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BORROWING CONSTRAINTS AND CREDIT DEMAND IN A DEVELOPING ECONOMY

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SUMMARY

This paper investigates the determinants of credit demand in the presence of borrowing constraints in a developing economy. We model the determinants of observed debt for Chilean households while accounting for selection bias and the endogeneity of their income and specific household assets. Using a novel Chilean dataset, we estimate the relationship between household characteristics and consumer and mortgage debt. We find substantial differences in the nature of these relationships across the types of debt. For example, we find that the income elasticity for consumer debt is greater than 1 whereas for mortgage debt it is not. The results suggest the increased availability of credit, combined with the aging of the Chilean population, is likely to drastically change the distribution and level of Chilean debt. These findings are particularly relevant for other developing economies currently experiencing rapid income and debt growth.Copyright © 2015 John Wiley & Sons, Ltd.

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1. INTRODUCTION

The process of financial deepening in developing countries has substantially increased the availability of credit in their economies. However, while there are a number of studies for developed economies such as the USA and Italy, relatively little is known about the demand for credit in developing economies using balance sheets from representative surveys. A first step in understanding the potential impact of the deregulation of financial markets is determining the factors driving the level of household debt. By establishing these factors in a situation where households are credit constrained, while accounting for them being constrained, we gain some insight into how the level of demand for credit might respond when the constraints are relaxed. In this paper we examine the demand for credit in Chile, a country of particular interest given its recent rapid growth in its level of income and access to credit.

Identifying these determinants, and their impact, provides insight into a number of important economic questions. For example, how does the household credit demand vary over the life cycle of the household head? Also, what is the income elasticity of the demand for credit and how does it vary by location in the income distribution? In addition, there is also a great deal to be learnt about issues related to household consumption. The demand for debt in Chile is of particular interest given that many of the changes occurring there, with respect to credit access, are likely to occur in other Latin American countries. The financial deepening process in Chile can be described by a level of 'debt to GDP' of 25% in 2007.[1] This compares to figures in the range of 20–90% for developed economies.[2] Banking debt held by households represented more than 70% of total household debt in 2007 and grew by almost 15% in average real annual terms between the years 2003 and 2007. The 2000s have

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[1] Note that as the microdata set we examine is based on information gathered in 2007, we focus our introductory discussion on the same period.

[2] IMF's Global Financial Stability Report 2006–2012. See also Djankov *et al.* (2007) for additional international comparisons.

also seen the growth in total household debt surpass the growth in disposable household income. thereby significantly increasing the ratio of debt to disposable income. This ratio went from 44% in 2003 to 67% in 2007. Furthermore, the financial service burden to disposable income ratio increased from 14% to 20%. Since banking debt is the most important component of household debt, this increased exposure of the banking system to household sector is a matter of concern from a financial stability perspective. Banking exposure, measured as the sum of total mortgage and consumer loans as a percentage of total banking loans, increased from 15% at the beginning of the 1990s to over 30% in 2007.

There is widespread access to credit among Chilean households. While only 21% of households held some mortgage, 63% held some consumer loan in 2007. However, while mortgage holding is more prevalent in middle- to high-income households, consumer debt holding is widespread among all income groups. By 2007, the financial sector had been growing at a very rapid pace. The number of bank branches and corresponding employees had increased above 10% per year, and the number of bank credit cards had grown by more than 25% per year. In 2008, the number of existing credit cards, both bank and non-bank credit cards, was more than 19 million—more than one per capita—where 50% was offered by retailers and other non-bank credit suppliers. Also, by 2008 there were 11 large retail chains with national geographic coverage in Chile and a total of 482 retail stores throughout the country. These chains had a concentration of 61% of the sales of durable goods, issued more than 77% of credit cards and supplied more than 40% of the non-banking credit held by households.

Overall, household credit in Chile increased steadily at a rate above 20% per year during the 2000s, as per capita income grew from US $5000 in 2000 to US $12,000 in 2010 in nominal terms. With a similar level of per capita income, countries such as Colombia and Peru are currently exhibiting credit growth rates above 16% and 24% respectively,[3] noting that while in Colombia consumer credit is growing faster than mortgage credit, the opposite is occurring in Peru. In investigating the determinants of credit demand a number of econometric obstacles arise. First, households only report positive credit levels when they demand positive levels of credit *and* they find a willing lender. Thus, looking at the determinants of credit demand for a sample of households with positive levels of credit presents a 'sample selection problem'. Second, two important determinants of the desired level of credit are the individual's income and asset holdings. However, these variables are potentially jointly determined with credit. Thus it is necessary to account for these selection and endogeneity biases.

In estimating models contaminated by selection/endogeneity due to unobserved heterogeneity, an important issue which must be confronted is the source of identification. In the model below we account for selection bias arising from two forms of censoring in addition to the endogeneity of two key explanatory variables. Thus, for the purpose of identifying the credit demand equation parameters we need a number of exclusion restrictions. While the nature of the model we estimate allows the imposition of some exclusions, we also rely on a unique feature of the Chilean credit structure to obtain a series of variables which affect the household's access to credit but not the level of individual household demand. More explicitly, we exploit geographical variation in the access to credit through bank and retail stores, focusing on their availability within a certain area. We observe that location decisions of both banks and retail stores are driven by local aggregate variables such as urban density, and demographic, socioeconomic and commercial activity. This access to credit does not reflect any aspect of individual household level demand.

We acknowledge that a study which focuses on the life cycle patterns of credit, and how the household's employed level of credit respond to income shocks, is best performed using panel data which follow the same households over time. Panel data are particularly useful when the objective is to characterize or estimate dynamic relationships of interest. While some of the issues we confront below might be better handled via panel data, we are unable to do so as there are no appropriate datasets for

[3] Debt and GDP figures from respective Central Banks.

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Chile. However, while noting some aspects of our study might be enhanced through the use of panel data, we highlight that the cross-sectional data we employ is remarkable due to its detailed information on the households' balance sheets. Moreover, due to the variation featured in the data with respect to households' age, income and regional location, there is a great deal one can learn about how the demand for credit responds to these factors in a static setting.

In addition to the econometric problems noted above, there are two important measurement issues. The first is the definition of 'credit constrained'. Although alternative definitions exist, we use the most commonly employed (see, for example, Jappelli, 1990; Cox and Jappelli, 1993; Gropp, *et al.* 1997; Jappelli, 1998; Ferri and Simon, 2002; Crook 2006). We consider a household to be credit constrained if it was either rejected or discouraged from applying for credit. Other studies have adopted alternative measures. Zeldes (1989) defined credit constraints on the basis of the individual's level of assets. Jappelli (1990) and Bertaut and Haliassos (2005) define individuals as credit constrained if their demand for credit is higher than the supply of credit they face. Gross and Souleles (2002) define as credit constrained those who cannot access low-cost credit and thus resort to high-cost loans such as bank credit cards. Our preference for our measure is motivated by its simplicity, which is likely to reduce measurement error. It also enables comparisons with other countries owing to its frequent use (see (Crook, 2006)).

The second measurement issue is related to debt. While mortgage debt comprises a substantial share of total debt in developed countries, it is likely to be less important in developing countries, where home ownership is less common[4] and the houses generally have lower value compared to per capita GDP. For example, while in developed economies aggregate mortgage debt-to-income ratio is often above 100%, in developing countries it is closer to 50%.[5] Hence it is preferable to separately analyze the different types of debt as they may respond differently to the various determinants and credit constraints. Accordingly, we estimate separate models for consumer debt, mortgage debt and total debt.

The following section introduces the data we employ and provides some empirical background on Chilean debt holding and borrowing constraints. Section 3 provides the empirical models explaining whether households are credit constrained and hold debt respectively. Section 4 presents the estimation results regarding the determinants of debt level. Section 5 provides some concluding comments.

2. STYLIZED FACTS OF DEBT HOLDING AND BORROWING CONSTRAINTS IN CHILE

Our analysis employs the Chilean Survey of Households Finances (ChSHF) data collected by the Central Bank of Chile. The survey elicits detailed information on the household's labor market status, real estate ownership, financial assets, debts, its perceptions regarding debt service, access to credit, pensions, insurances and savings. The ChSHF was conducted in 2007 and included 4021 households at the urban national level (87% of the population in Chile). The survey has an oversampling of wealthier households as many assets are held by only a small fraction of the population.[6] The ChSHF 2007 is the only statistical source in Chile that provides complete information on the balance sheets of households and their ability to service financial commitments.

It is worth noting some peculiarities of the Chilean mortgage market. Although home ownership reaches about 71%, only 21% of households have a mortgage. Among them, almost half receive some sort of state-provided subsidy. Moreover, households can access relatively low interest rates through private banks, with interest rates below 8%. In this context, the data reveal that 65% of total debt is mortgage debt, noting that we exclude informal credit from our analysis (which is less than 10% of

[4] Home ownership is 71% in Chile, compared to a median of 78% in developed economies, according to Eurostat.

[5] IMF's Global Financial Stability Report 2006–2012 and Djankov *et al.* (2007).

[6] The sample design of the ChSHF was developed in collaboration with the Tax Office, following the sample design of the Survey of Consumer Finances in the USA. See Banco Central de Chile (2009).

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Table I. Distribution of debt and credit constraints

	Income share	Total debt share	Mortgage debt share	Consumer debt share	Households w/any debt	Households w/mortgage debt	Households w/consumer debt	Constrained households
Percentage points								
By income quintiles								
I	2.3	4.1	3.2	5.9	46.5	7.0	42.6	21.1
II	5.4	5.6	3.9	8.7	61.0	9.6	58.1	20.6
III	9.4	8.3	6.7	11.3	65.1	15.0	59.6	16.5
IV	17.3	25.3	23.7	28.3	69.3	27.5	62.1	16.5
V	65.6	56.7	62.6	45.8	71.3	45.2	58.2	10.7
By age								
18–24	1.6	0.5	0.3	0.9	61.3	4.7	59.4	21.7
25–34	11.2	14.8	15.8	12.8	71.3	21.5	65.5	20.0
35–44	24.7	33.1	38.5	23.2	72.9	33.3	63.1	17.9
45–54	28.1	31.2	31.0	31.6	68.9	25.1	60.5	18.2
55–64	21.1	17.0	12.7	24.8	60.2	18.9	54.9	17.8
65+	13.3	3.5	1.8	6.7	38.5	4.8	35.9	11.2
By education [a]								
Primary	15.6	11.7	7.7	19.0	52.8	8.9	49.7	20.1
Secondary	34.9	35.0	31.7	40.9	66.0	20.3	59.2	17.3
Tertiary	49.5	53.4	60.5	40.2	69.5	37.9	58.9	12.6
By region								
North	4.8	4.7	3.4	7.0	75.1	21.0	70.8	21.7
Center	18.6	17.6	15.3	21.8	60.6	18.2	54.9	14.9
South	6.7	6.8	6.3	7.7	65.5	20.3	60.0	18.1
Metrop	69.9	71.0	75.1	63.5	61.5	21.9	54.3	17.3
Total	100.0	100.0	100.0	100.0	62.6	20.9	56.1	17.1

Source: EFH 2007.
[a] Primary is 0–6 years of education; secondary is 7–12 years of education; and tertiary is 13 and more years of education.

consumer debt).[7] Moreover, the distribution of each component of total household debt appears similar to that of household income. Table I indicates that this is true across income groups, age groups, educational levels and geographical regions as highly educated, middle-aged, wealthy households concentrated in the Metropolitan region hold the vast majority of income and debt. The richest quintile holds 66% of income and 57% of total debt (46% of consumer debt and 63% of mortgage debt). Household heads aged between 35 and 54 years hold 53% of income and 64% of total debt (55% of consumer debt and 70% of mortgage debt).

Table I indicates that 63% of households hold some debt (last row), 56% hold consumer debt and only 21% hold mortgage debt. Thus, while mortgage debt holding appears to be related to high-income groups, consumer debt appears to be held by all income groups (columns 6 and 7, first panel of Table I). Mortgage debt holding exhibits the life cycle inverted U-shaped profile, while the consumer debt profile is relatively age invariant (second panel in Table I). Debt holding by education appears to be linked to income. That is, tertiary educated household heads are more likely to hold a mortgage credit than those less educated. However, household consumer debt holding appears independent of the household head's education level. Finally, little variation is found for either mortgage or consumer debt holdings across the aggregate geographical areas.

The definition of being credit constrained is based on the questionnaire of the ChSCF, which follows (not exactly) the US Survey of Consumer Finances. The exact wording in the ChSHF is:

[7] This estimate of 65% is consistent with the evidence provided by the Central Bank of Chile. Note that mortgage debt in the USA is about 80% of total debt and in Italy it is 60% (Crook, 2006).

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'*How many credit applications have you filled out in the last two years? (Including refinancing)*'; '*How many credit applications have been rejected?*' We classify those who have had applications rejected as 'credit constrained'. Those that answered zero to credit applications filled out were asked, '*Why you did not apply for credit?*', to which they could respond '*1. Don't need it; 2. Don't like to apply for credit; 3. Could not pay back; 4. They would not grant it; 5. Already have a credit; 6. Other reason*'. Those who answered alternative 4 were classified as 'discouraged borrowers' and added to the 'credit-constrained' group. Using this definition, the last column of Table I reveals that while less than 11% of top-income quintile households are credit constrained, more than 20% of the bottom two quintiles of households are constrained. Similarly, less than 13% of households with tertiary education are credit constrained. For households with primary education it is more than 20%. Also, the unconditional probability of being credit constrained decreases with age.

Some interesting geographical patterns also emerge. We classified as Northern regions I–III, where most of the mining activity occurs; Metropolitan region where the capital Santiago is located; Center regions IV–VII (except the Metropolitan region), where most of the agricultural-related activities predominate; and Southern regions VIII–XII, where most of the forestry activities are located. While Northern regions have above average levels of credit constraints (almost 22%), the Center and Metropolitan regions have below-average levels (15% and 17% respectively). In parallel, the majority of income and debt is held in the Metropolitan region.

Despite these geographical peculiarities, the distribution of debt and the presence of credit constraints appear to be highly related to the distribution of income and educational levels. However, access to some credit (positive debt) seems to be widely distributed across households. The age of the household head also plays a role with inverted U-shaped profiles for debt share and debt holding. The age of the household head has a negative relationship for credit constraints.

The estimate that 17% of Chilean households are credit constrained should be treated cautiously. Using the Gross and Souleles (2002) definition, in which a household is considered credit constrained if it uses high-cost credit, Ruiz-Tagle (2009) finds that at least 29% of Chilean households were credit constrained in 1988. The corresponding figures for 1997 and 2004 are 21% and 41% respectively. Using this definition, Gross and Souleless find that about two-thirds of the US population would be credit constrained between 1995 and 1998. An additional comparison is provided by Grant (2007) for the USA between 1988 and 1993, who finds that between 26% and 31% of the population were credit constrained. Crook and Hochguertel (2007) estimated credit constraints in the 1990s and 2000s at 2.4–3.7% for the Netherlands, 2.7–3.3% for Italy and 3.4% for Spain in 2004. Thus, while the 17% estimate is low compared to US figures, it is much larger than available estimates for European countries.[8]

Finally, we focus on debt holding and credit constraints simultaneously. This is important to motivate the empirical approach below, where debt demand occurs after selection of those who decide to hold debt and are not credit constrained. We define two binary variables to assess this issue: $B = 1$ if the household holds the corresponding type of debt, and 0 otherwise; and $N = 1$ if household is credit unconstrained, and 0 otherwise. Table II shows that 51% of households are unconstrained debt holders. Only 5.5% are constrained non-debt holders, and 11.6% are constrained debt holders. This suggests that relaxing borrowing constraints would affect a relatively small number of households at

[8] In making international comparisons of the estimates of credit constraints it is necessary to compare survey questionnaires on which they are based. For example, the questionnaires refer to the 2 years preceding the survey in the Netherlands and Spain, 1 year in Italy, and 5 years in the USA. In the Chilean case, the questionnaire refers to last 2 years. The inclusion of 'discouraged borrowers' as credit-constrained households implies another source of complexity for international comparisons. For example, in the US and in the Netherlands it is possible for a household to have applied for a credit and to have been discouraged, whereas in Italy, Spain and Chile the questionnaire does not allow this. A household may only be discouraged if it did not apply for a loan (see wording of questionnaire above).

Table II. Prevalence of borrowing and credit constraints

	Constrained ($N = 0$)	Unconstrained ($N = 1$)	Total
Percentages			
Consumption debt			
Non Debt Holder ($B = 0$)	6.0	37.9	43.9
Debt Holder ($B = 1$)	11.1	45.0	56.1
Mortgage debt			
Non-debt holder ($B = 0$)	13.7	65.5	79.1
Debt holder ($B = 1$)	3.4	17.4	20.9
Any debt			
Non-debt holder ($B = 0$)	5.5	31.9	37.4
Debt holder ($B = 1$)	11.6	51.0	62.6
Total	17.1	82.9	100.0
Number of observations			
Consumption debt			
Non-debt holder ($B = 0$)	229	1447	1676
Debt holder ($B = 1$)	424	1717	2141
Mortgage debt			
Non-debt holder ($B = 0$)	522	2499	3021
Debt holder ($B = 1$)	131	665	796
Any debt			
Non-debt holder ($B = 0$)	210	1217	1427
Debt holder ($B = 1$)	443	1947	2390
Total	653	3164	3817

Source: EFH 2007.
Note: $B = 1$ if household holds the corresponding type of debt (0 otherwise); $N = 1$ if household is credit unconstrained (0 otherwise).

the extensive margin.[9] Since 13.7% of households are constrained non-mortgage debt holders, this suggests it would affect mortgage credit more than consumer credit.

These characteristics of the credit situation among households indicate that a more profound financial deepening process could play a limited role in increasing borrowing levels, at least at the extensive margin. It also appears the most important factor related to the decision to borrow is income. Moreover, larger income shares are associated with larger debt shares. Nevertheless, the intensive margin at which households borrow needs the analysis of credit demand. This is addressed below.

3. WHICH HOUSEHOLDS ARE UNCONSTRAINED AND HOLD DEBT?

Our primary objective is to uncover the determinants of household debt. However, to overcome the inherent selection issues and endogeneity issues we adopt a control function approach which requires the estimation of some preliminary equations. As these equations are also of interest we first discuss the results from each of them. We begin with a model explaining whether the household is borrowing constrained. The model has the form

$$N_i = I(X_{Ni}\beta_N + u_{Ni} > 0) \tag{1}$$

[9] We use the term 'extensive margin' to refer to the decision to borrow or not borrow and the term 'intensive margin' to describe the amount of borrowing for those borrowing positive amounts.

Table III. Summary statistics of variables (means)

Variables	All	Constrained	Unconstrained	Any debt holders	Mortgage debt holders	Consumer debt holders	Non-debt holders
No. of observations	3817	653	3164	2390	796	2141	1427
Any debt holder = 1	0.63	0.68	0.62	1	1	1	0
	(0.48)	(0.47)	(0.49)	(0.00)	(0.00)	(0.00)	(0.00)
Mortgage debt holder = 1	0.21	0.2	0.21	0.33	1	0.26	0
	(0.41)	(0.40)	(0.41)	(0.47)	(0.00)	(0.44)	(0.00)
Consumer debt holder = 1	0.56	0.65	0.54	0.9	0.69	1	0
	(0.50)	(0.48)	(0.50)	(0.31)	(0.46)	(0.00)	(0.00)
Any debt	5.53	5.78	5.48	8.84	21.09	7.72	0
	(13.43)	(13.13)	(13.49)	(16.09)	(21.78)	(14.87)	(0.00)
Mortgage debt	3.58	2.96	3.71	5.72	17.16	4.24	0
	(11.34)	(9.79)	(11.64)	(13.90)	(19.60)	(11.80)	(0.00)
Consumer debt	1.95	2.83	1.77	3.12	3.92	3.48	0
	(5.75)	(7.25)	(5.38)	(7.02)	(8.30)	(7.33)	(0.00)
Unconstrained = 1	0.83	0	1	0.81	0.84	0.8	0.85
	(0.38)	(0.00)	(0.00)	(0.39)	(0.37)	(0.40)	(0.35)
Annual income	32.02	24	33.67	33.95	55.4	31.95	28.78
	(56.00)	(44.50)	(57.95)	(53.82)	(72.77)	(51.95)	(59.34)
Total assets	100.67	54.01	110.3	103.89	177.58	91.36	95.28
	(243.69)	(97.95)	(262.91)	(206.36)	(248.20)	(184.01)	(295.85)
Real estate assets	85.07	45.97	93.14	89.2	151.98	79.2	78.16
	(218.45)	(84.10)	(236.08)	(181.16)	(215.82)	(166.02)	(269.52)
Non-real estate assets	15.6	8.04	17.17	14.7	25.6	12.16	17.12
	(72.23)	(34.07)	(77.73)	(56.95)	(73.43)	(44.26)	(92.34)
Age	50.11	48.16	50.51	47.42	45.48	47.54	54.61
	(15.21)	(14.77)	(15.28)	(13.48)	(10.56)	(13.73)	(16.82)
Years of education	12.08	11.49	12.2	12.58	14.35	12.43	11.23
	(4.95)	(4.74)	(4.98)	(4.78)	(4.53)	(4.76)	(5.11)
Gender (male = 1)	0.62	0.61	0.62	0.64	0.66	0.65	0.57
	(0.49)	(0.49)	(0.49)	(0.48)	(0.47)	(0.48)	(0.50)
No. of persons in household	3.53	3.76	3.48	3.75	3.83	3.74	3.16
	(1.69)	(1.76)	(1.68)	(1.65)	(1.56)	(1.63)	(1.71)
Spouse present = 1	0.65	0.65	0.65	0.7	0.77	0.69	0.56
	(0.48)	(0.48)	(0.48)	(0.46)	(0.42)	(0.46)	(0.50)
No. of employed persons in household	1.56	1.63	1.54	1.69	1.77	1.69	1.34
	(1.00)	(1.03)	(1.00)	(0.96)	(0.87)	(0.96)	(1.05)
Unemployed	0.02	0.03	0.02	0.02	0.02	0.02	0.02
	(0.14)	(0.16)	(0.13)	(0.14)	(0.14)	(0.15)	(0.13)
Employed	0.77	0.80	0.76	0.83	0.90	0.83	0.65
	(0.42)	(0.4)	(0.43)	(0.37)	(0.3)	(0.38)	(0.48)
Signed job contract	0.47	0.44	0.47	0.54	0.62	0.53	0.35
	(0.5)	(0.5)	(0.5)	(0.5)	(0.49)	(0.5)	(0.48)
Wage earner	0.50	0.51	0.50	0.57	0.61	0.57	0.38
	(0.5)	(0.5)	(0.5)	(0.49)	(0.49)	(0.49)	(0.48)
Self-employed	0.18	0.20	0.18	0.17	0.16	0.17	0.20
	(0.38)	(0.4)	(0.38)	(0.37)	(0.37)	(0.37)	(0.4)
Area income	35.92	31.13	36.91	36.25	43.79	35.23	35.37
	(22.86)	(20.12)	(23.27)	(23.25)	(24.74)	(22.82)	(22.19)
Northern region	0.07	0.09	0.07	0.09	0.07	0.09	0.05
	(0.26)	(0.29)	(0.25)	(0.28)	(0.26)	(0.29)	(0.22)

Table III. Continued

Variables	All	Constrained	Unconstrained	Any debt holders	Mortgage debt holders	Consumer debt holders	Non-debt holders
Center region	0.23 (0.42)	0.2 (0.40)	0.23 (0.42)	0.22 (0.42)	0.2 (0.40)	0.22 (0.42)	0.24 (0.43)
Southern region	0.08 (0.27)	0.09 (0.28)	0.08 (0.27)	0.08 (0.28)	0.08 (0.27)	0.09 (0.28)	0.07 (0.26)
Metropolitan region	0.62 (0.49)	0.62 (0.49)	0.62 (0.49)	0.61 (0.49)	0.65 (0.48)	0.6 (0.49)	0.63 (0.48)
Inhabitants over no. of banks by region	2138.42 (494.68)	2185.81 (494.73)	2128.64 (494.18)	2105.12 (521.49)	2141.44 (512.20)	2097.47 (526.98)	2194.18 (440.77)
Inhabitants over no. of banks by municipality	3755.25 (3222.87)	3800.2 (3182.23)	3745.97 (3231.62)	3826.23 (3391.54)	3793.11 (3223.21)	3855.95 (3475.22)	3636.38 (2915.91)
No. of retail stores by municipality	5.21 (6.25)	5.55 (6.51)	5.15 (6.19)	5.19 (5.84)	5.10 (5.49)	5.23 (5.93)	5.26 (6.88)
No. of retail stores by region	86.81 (47.75)	86.98 (48.07)	86.77 (47.7)	85.25 (48.54)	89.35 (47.42)	84.32 (48.79)	89.42 (46.3)
Self-perception: financial service high	0.29 (0.45)	0.43 (0.50)	0.26 (0.44)	0.29 (0.45)	0.22 (0.41)	0.3 (0.46)	0.29 (0.45)
Had delayed payments in past 12 months	0.17 (0.38)	0.32 (0.47)	0.14 (0.35)	0.24 (0.43)	0.19 (0.39)	0.26 (0.44)	0.07 (0.25)
No. of arrears in past 12 months	0.52 (1.83)	1.2 (2.78)	0.38 (1.52)	0.75 (2.16)	0.57 (1.83)	0.82 (2.25)	0.14 (0.95)
No. of formal arrears in past 12 months	0.45 (2.33)	1.21 (4.68)	0.29 (1.37)	0.65 (2.84)	0.59 (3.89)	0.7 (2.97)	0.11 (0.92)
No. of checks rejected to pay in past 12 months	0.14 (1.01)	0.35 (1.58)	0.09 (0.83)	0.2 (1.22)	0.19 (1.16)	0.21 (1.26)	0.03 (0.45)
No. of insurances held by household	0.75 (1.24)	0.66 (1.20)	0.77 (1.25)	0.91 (1.34)	1.42 (1.63)	0.88 (1.32)	0.48 (1.00)
Amount of pension fund of household head	15.74 (29.30)	13.88 (28.01)	16.13 (29.55)	19.84 (32.12)	27.6 (37.23)	19.32 (31.36)	8.89 (22.23)
Current account owner = 1	0.36 (0.48)	0.26 (0.44)	0.38 (0.49)	0.41 (0.49)	0.64 (0.48)	0.39 (0.49)	0.28 (0.45)
Uses telebanking = 1	0.27 (0.45)	0.23 (0.42)	0.28 (0.45)	0.33 (0.47)	0.52 (0.50)	0.32 (0.47)	0.18 (0.38)
Dummy pension fund (> 0 = 1)	0.56 (0.50)	0.6 (0.49)	0.55 (0.50)	0.66 (0.47)	0.72 (0.45)	0.67 (0.47)	0.38 (0.49)

Note: Standard deviations in parentheses.

where N_i is an indicator which takes value 1 if the household reports it is borrowing unconstrained and the value 0 otherwise; the X_{Ni}s are exogenous variables, β_N is an unknown parameter vector and u_{Ni} are zero mean error terms. The model is estimated via least squares methods (linear probability model), noting that we allow for nonlinearities between the continuous explanatory variables and the dependent variable. Thus the model has a semi-parametric flavor, although estimation is based on the least squares criterion. The X_N vector includes the variables which are considered exogenous to the system. Although we acknowledge that the 'control function' estimator we employ below requires that

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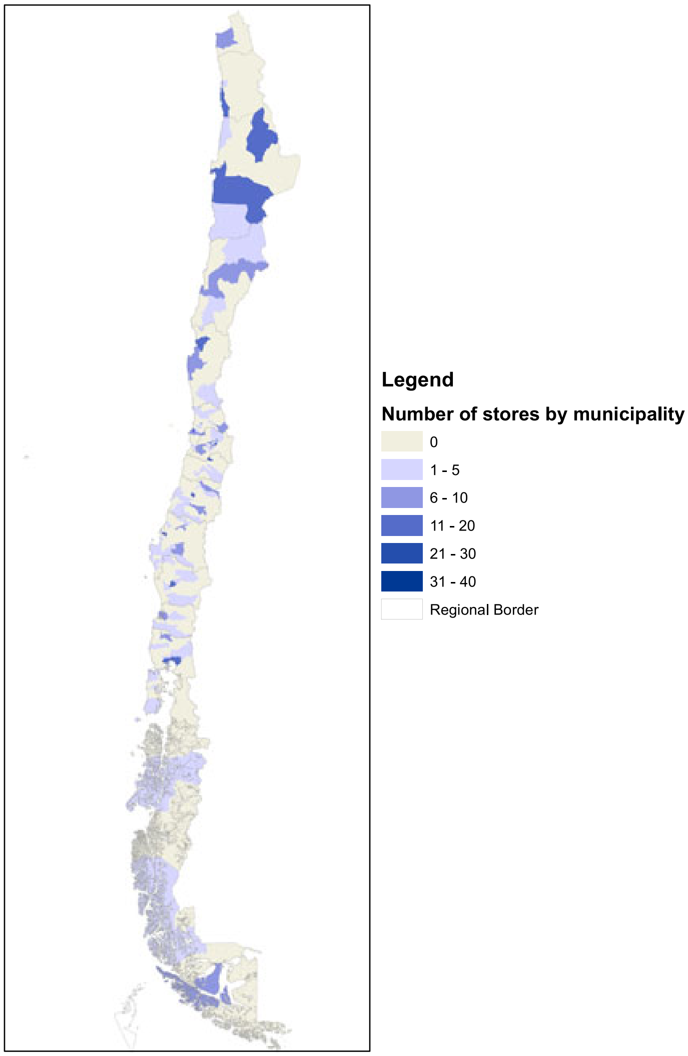

Figure 1. Access to retail stores: Geographical variation of stores by municipality

the propensity scores explaining the respective selection rules are appropriately modeled, we prefer a neutral approach to selecting the Xs.

This approach requires the imposition of exclusion restrictions for identification. That is, we require variables which appear in equation (1) but do not appear in the debt-level equation that we discuss below. The variables we employ are related to credit accessibility—more explicitly, the number of banks and the number of retail stores at the local level. We use the ratio of the number of inhabitants per number of banks and the number of retail stores present in each municipality and in each region as proxies for financial depth. These variables are related to the facility to access the financial system in each area. Note that the location decisions of both banks and retail stores are driven by local aggregate variables such as urban density, demographic, socioeconomic and commercial variables (access to services, transportation, space availability and price). For example, in Chile, the location of malls and large retail stores is explicitly aimed to attract an expected amount of revenue per year, and the models used to project these amounts are based precisely on these types of variables aggregated at the

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municipality level (Galetovic *et al.*, 2009). Hence these variables do not reflect any aspect of individual household-level demand.

The identification strategy also requires sufficient variability of the variables related to access to credit. Table III reports substantial variation in the variables related to the bank system availability and retail stores proximity, both at the regional level and at the municipality level. While the minimum is six banks in a region, in some regions there are 26. Similarly, the minimum is six retail stores within a region and the maximum is 124. Even at the municipality level there is significant variation. In this dimension the number of banks ranges from 1 to 23, and the number of retail stores from 0 to 32. (Figure 1 shows the variation at the municipality level that is observed among retail stores allocation.)

In addition to these access measures the X_N vector includes age, education and income (measured as annual total household income in thousands of US dollars,[10]) real estate assets, dummy variables for gender (1 if male), spouse (1 if spouse present in household), total number of people in household and total number of employed individuals in household. Unemployment of the household head is also included (1 if unemployed), as is the average area income at the municipality level to capture geographical income segregation and regional controls.

Before turning to the estimates of equation (1), consider some features of the data shown in Table III. Many indebted households have relatively low debt and the dispersion of debt is relatively high. This is particularly true for consumer debt. Non-real estate assets represent less than a fifth of real estate assets, indicating the majority of household wealth is real estate. Also, the proportion of households that report a self-perception that their 'financial service is high', including interest and principal, is 29%.[11]

The estimates for equation (1) are presented in column 1 of Table IV. Real estate assets, education, area income and 'having signed a job contract', statistically significantly increase the probability of being unconstrained. These variables are related to permanent income and suggest that borrowing constraints decrease as permanent income increases. The coefficient for education is small and only statistically significant at the 10% level. However, real estate assets have a strong and statistically significant effect. For example, an increase in real estate assets of US \$1000 would increase the probability of being unconstrained by 9%, while 'signing a job contract' would increase the probability by 3.3%.

We include real estate assets as a measure of wealth. The variable is defined as the 'total value of home plus other real estate assets'. One may be concerned that this is determined simultaneously with mortgage debt but, as we noted above, while 71% of households report real estate assets only 21% hold mortgage debt.

The results also suggest unemployed households heads are less likely to be credit constrained but the result is not statistically significant. This suggests there is no evidence of consumption smoothing. However, the question in the survey about being unconstrained refers to the previous 2 years, whereas that for unemployment refers to the contemporaneous state. Self-perception of paying high financial services reduces statistically significantly the probability of being unconstrained, showing that the credit scoring process may capture well indebtedness self-perception. Age exhibits a concave profile, although the coefficients are not statistically significant. Geographical controls (North, Center and South) do not show any significant effect, suggesting that regional heterogeneity is probably captured by other variables which vary by region. Variables indicating whether the individual had delayed payments and number of arrears (i.e. 'had delayed payments in the last 12 months', 'number of arrears in the past 12 months', 'number of formal arrears in the past 12 months') have a negative impact

[10] Conversions rate to US dollars is nominal.

[11] This is a simple self-assessment by the respondent concerning household financial stress. Interviewees are asked '*How would you rate your level of indebtedness?*' We construct a dummy variable that equals 1 if the individual responds '*Excessive*' or '*High*'.

Table IV. Estimates for selection and endogenous variables models

Variable	(1) Unconstrained =1	(2) Positive Consumer Debt =1	(3) Positive Mortgage Debt =1	(4) Positive Total Debt =1	(5) Annual Total Income	(6) Non-real Estate Assets
Real estate assets	8.98e−05*** (2.93e−05)	−9.22e−05** (3.67e−05)	0.000109*** (2.97e−05)	−7.46e−06 (3.52e−05)		
Years of education	0.00251* (0.00144)	−0.000159 (0.00180)	0.00385*** (0.00146)	0.000817 (0.00172)	1.215*** (0.192)	0.519* (0.275)
Spouse present = 1	−0.000205 (0.0151)	0.0335* (0.0190)	0.0669*** (0.0154)	0.0569*** (0.0182)	1.506 (2.023)	1.527 (2.901)
Male = 1	−0.00429 (0.0141)	0.00969 (0.0176)	−0.0462*** (0.0143)	−0.0138 (0.0169)	4.197** (1.881)	4.801* (2.697)
Age	0.00178 (0.00247)	0.00241 (0.00310)	0.00769*** (0.00251)	0.00654** (0.00297)	0.688** (0.330)	−0.204 (0.474)
Age^2	−7.58e−06 (2.36e−05)	−4.86e−05 (2.96e−05)	−9.59e−05*** (2.39e−05)	−9.86e−05*** (2.83e−05)	−0.00459 (0.00315)	0.00270 (0.00452)
No. of persons in household	−0.00695 (0.00447)	0.00738 (0.00560)	0.00353 (0.00454)	0.00971* (0.00537)	1.543*** (0.597)	−0.603 (0.857)
No. of employed persons in household	−0.00237 (0.00749)	0.0200** (0.00939)	−0.0122 (0.00761)	0.0150* (0.00900)	4.437*** (1.001)	0.374 (1.436)
Unemployed = 1	−0.0102 (0.0451)	0.0387 (0.0565)	0.0560 (0.0457)	0.0112 (0.0542)	−1.108 (6.024)	−6.778 (8.640)
Signed job contract	0.0330** (0.0158)	−0.00433 (0.0198)	0.0192 (0.0160)	−0.00644 (0.0190)	−0.411 (2.110)	−0.0265 (3.027)
Self-employed	−0.000451 (0.0179)	−0.0429* (0.0224)	0.00230 (0.0181)	−0.0408* (0.0215)	−0.0249 (2.388)	0.788 (3.425)
Area income	0.000942*** (0.000300)	−0.00101*** (0.000377)	0.00111*** (0.000305)	−0.000441 (0.000361)	0.366*** (0.0400)	0.212*** (0.0574)
North (1)	0.0395 (0.114)	−0.131 (0.143)	0.0189 (0.116)	−0.120 (0.137)	20.05 (15.26)	59.56*** (21.89)
Center (1)	0.0730 (0.0957)	−0.244** (0.120)	−0.0343 (0.0972)	−0.231** (0.115)	18.98 (12.80)	60.66*** (18.35)
South (1)	0.0465 (0.114)	−0.210 (0.143)	0.00675 (0.116)	−0.194 (0.137)	27.08* (15.28)	63.13*** (21.92)
Self-perception: financial service high	−0.0870*** (0.0137)	0.0199 (0.0171)	−0.0363*** (0.0139)	−0.00550 (0.0164)	2.758 (1.825)	9.239*** (2.618)
Had delayed payments in past 12 months	−0.0762*** (0.0205)	0.236*** (0.0257)	0.0313 (0.0208)	0.208*** (0.0246)	−2.098 (2.741)	−4.420 (3.931)
No. of arrears in past 12 months	−0.00868* (0.00498)	0.0130** (0.00625)	−0.00541 (0.00506)	0.00936 (0.00599)	−1.452** (0.666)	−0.596 (0.956)
No. of formal arrears in past 12 months	−0.0105*** (0.00319)	0.00124 (0.00400)	0.00819** (0.00324)	0.00286 (0.00384)	0.177 (0.427)	0.147 (0.612)
No. of checks rejected to pay in past 12 months	−0.00519 (0.00686)	0.000641 (0.00860)	0.00747 (0.00697)	0.000774 (0.00824)	0.894 (0.917)	0.348 (1.316)
No. of insurances held by household	−0.0101* (0.00569)	0.0301*** (0.00714)	0.0343*** (0.00578)	0.0283*** (0.00684)	7.086*** (0.754)	5.608*** (1.082)
Amount of pension fund of household head	1.58e−05 (0.000252)	0.000405 (0.000316)	0.000843*** (0.000256)	0.000617** (0.000303)	0.0783** (0.0337)	0.183*** (0.0483)
Dummy pension fund (> 0 = 1)	−0.0260* (0.0150)	0.135*** (0.0188)	0.0380** (0.0152)	0.139*** (0.0180)	−4.050** (1.998)	−4.435 (2.866)
Current account owner = 1	0.0382** (0.0167)	0.0114 (0.0209)	0.0927*** (0.0169)	0.0312 (0.0200)	16.97*** (2.218)	15.95*** (3.181)

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Table IV. Continued

Variable	(1) Unconstrained =1	(2) Positive Consumer Debt =1	(3) Positive Mortgage Debt =1	(4) Positive Total Debt =1	(5) Annual Total Income	(6) Non-real Estate Assets
Uses telebanking = 1	−0.0227	0.0915***	0.0833***	0.0998***	9.083***	0.286
	(0.0173)	(0.0216)	(0.0175)	(0.0207)	(2.306)	(3.307)
Inhabitants over no. of banks by municipality	−5.96e−05***	−7.43e−05***	−7.40e−08	−7.51e−05***	0.000487	0.00423
	(1.72e−05)	(2.15e−05)	(1.74e−05)	(2.06e−05)	(0.00230)	(0.00329)
Inhabitants over no. of banks by region	−7.47e−08	7.83e−06***	7.14e−06***	7.53e−06***	−0.000460*	−0.000218
	(2.09e−06)	(2.62e−06)	(2.12e−06)	(2.51e−06)	(0.000279)	(0.000400)
No. of retail stores by municipality	−0.00124	−0.000251	0.00122	−0.000333	−0.183	−0.425**
	(0.00107)	(0.00134)	(0.00109)	(0.00129)	(0.143)	(0.205)
No. of retail stores by region	0.000761	−0.00211	−0.000248	−0.00189	0.224	0.562***
	(0.00108)	(0.00135)	(0.00109)	(0.00130)	(0.144)	(0.207)
Constant	0.812***	0.752***	−0.147	0.688***	−71.96***	−88.15***
	(0.143)	(0.179)	(0.145)	(0.171)	(19.05)	(27.32)
Observations	3817	3817	3817	3817	3817	3817
R^2	0.073	0.161	0.179	0.189	0.250	0.073

Note:Standard errors in parentheses. $^{**}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. (1) Metropolitan region excluded.

on the probability of being unconstrained. These may reflect the credit scoring process. Jointly, these variables produce a total effect of approximately −10%.

Now focus on the impact of our primary exclusion restrictions. The level of financial depth, measured as the number of inhabitants per number of banks, decreases the probability of being unconstrained (column 1). This is an interesting result in that financial deepening may play a role in reducing credit constraints among the population. Nevertheless, the variables capturing the availability of retail stores offering credit do not exhibit a statistically significant effect on the probability of being unconstrained. This is somewhat expected as the unconstrained characterization is more related to banks, through credit applications, rather than to retail stores offering credit cards where the constraint is probably the credit card limit.

Note that, in addition to the credit access variables, we employ some additional exclusion restrictions which are available owing to the detailed nature of the data. These are: (i) amount of pension fund of household head; (ii) whether the household head has a pension fund; (iii) whether the household head has a current account; and (iv) whether the household uses telebanking. Of these variables only the possession of a pension fund had a statistically significant effect on whether the household is credit constrained.

To estimate the demand for debt, we need to observe positive values of debt for unconstrained households. Accordingly, we estimate the following equation:

$$B_i = I(X_{Bi}\beta_B + u_{Bi} > 0) \tag{2}$$

where B_i is an indicator taking the value 1 if the household reports that it holds debt, the X_{Bi}s are exogenous variables, β_B is an unknown parameter vector and the u_{Bi} are zero mean error terms. The model is estimated in a similar manner to equation (1) and the results are shown in columns 2–4 of Table IV, noting that we estimate the model separately for different types of debt. The specification of the X_Bs is the same as equation (1).

A brief summary of these results is the following. The age of the household head has the expected concave profile for all types of debt. Real estate assets have a negative effect for consumer debt holding and a positive effect for mortgage debt holding. This highlights the earlier discussion regarding

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the role of real estate assets. Years of education is only statistically significant, and positive, for mortgage debt holding. The presence of the spouse of the household head has a positive effect on the probability of holding any type of debt. A male household head seems to be less likely to hold mortgage debt (−4.6%), but there is no statistically significant effect for consumer debt. Area income has a negative effect for consumer debt and positive effect for mortgage debt, suggesting some geographical segregation. Other regional controls are marginally statistically significant. Self-perception of over-indebtedness ('financial service is high') has a negative effect only for mortgage debt. Among the employment variables, total number of employed persons in household, as a proxy of household income stability, increases the probability of holding consumer debt, but has no statistically significant effect on mortgage debt. Self-employment reduces the probability of holding consumer debt. However, having signed a job contract, also as a proxy of labor income stability, exhibits no statistically significant coefficients.

The differences across the types of debt highlight the importance of analyzing each separately. This may reflect that, while consumer loans may be used to buy some durables, these are likely to be short-term durables. In contrast, mortgage debt might be seen as a long-term durable, which has little to do with short-term consumption behavior.

Consider the impact of our primary identifying variables on the probability of observing debt holdings. The measures of bank availability at the Municipality and Regional levels are statistically significant for both consumer debt and total debt (columns 2 and 4). However, the measures of availability of retail stores are not. For mortgage debt holding (column 3), only the availability of banks at the Regional level is statistically significant, whereas availability at the Municipality level is not. Overall, it appears that the variables are collectively explaining sufficient variation in these selection variables to suggest the model is identified. However, in addition to these variables, the additional exclusion restrictions discussed above, particularly the pension fund level and the use of telebanking, also appear to have some explanatory power.

4. ESTIMATING THE DETERMINANTS OF HOUSEHOLD DEBT

We now turn to estimating the determinants of the household debt level. We denote by D_i the logarithm of the debt (in thousands of US dollars). We noted above that only 63% of households report positive debt. Thus, if we estimated the determinants of debt level over these households, the possibility of sample selection bias arises. This is important as the development of the financial sector is likely to increase the number, and types, of households that are likely to take on debt. Accordingly, it is necessary to have estimates purged of selection.

Consider the following equation:

$$D_i = X_{Di}\beta_D + g_1(I_i) + g_2(A_i) + u_{Di} \tag{3}$$

where the X_{Di}s are exogenous variables, β_D is an unknown parameter vector, $g_1(\cdot)$ and $g_2(\cdot)$ are unknown functions, I_i and A_i capture the household's level of income and non-real estate assets respectively, and u_{Di} are zero mean error terms. Recall that we only observe unconstrained levels of debt if $N_i = 1$ and $B_i = 1$. Thus, for the sample of unconstrained debt holders, we rewrite the expectation of equation (3), assuming for now that I_i and A_i are exogenous, over the subsample for $N_i = 1$ and $B_i = 1$, as

$$E[D_i|N_i = 1\&B_i = 1] = X_{Di}\beta_D + g_1(I_i) + g_2(A_i) + E[u_{Di}|N_i = 1\&B_i = 1] \tag{4}$$

To obtain consistent estimates it is necessary to account for the misspecification of the conditional mean captured by the term $E[u_{Di}|N_i = 1\&B_i = 1]$. When the error terms u_{Di}, u_{Bi} and u_{Ni} are assumed to be jointly normal, it is straightforward to account for this misspecification. When the u_{Ni}s are uncorrelated with the u_{Bi}s this requires estimating each of equations (1) and (2) by probit and computing the inverse Mills ratio from each to be added as additional regressors in equation (3). If the u_{Ni}s are correlated with the u_{Bi}s, this requires the estimation of the correlation between these terms and thus the two equations must be estimated jointly rather than as two univariate probits (see Vella, 1998) in order to produce the appropriate control.

We allow for the correlation between the u_{Ni}s and the u_{Bi}s in addition to relaxing normality by employing the semiparametric methodology of Das *et al.* (2003). This procedure employs the following approximation:

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

where $f(\cdot)$ is an unknown function, $\Pr(\cdot)$ denotes probabilities which are estimated as the predicted values from the models in the previous section and X denotes the exogenous variables in the model. The $f(\cdot)$ function is approximated as a series polynomial which is determined by a cross-validation (CV) procedure.[12]

Estimation of the debt equation is complicated by inclusion of the household's income (I_i) and the household's non-real estate assets (A_i). First, each of these variables is likely to be endogenous to household debt. Second, it is restrictive to impose that these variables enter the debt equation linearly. Accordingly we follow Das *et al.* (2003) and include functions of the residuals from the reduced-form equations for these variables, denoted r_{Ii} and r_{Ai} respectively, as additional explanatory variables to control for the endogeneity. To capture the nonlinearity we add higher powers of the income and assets variables as additional regressors. To determine the 'appropriate' number of higher-order terms for each of these variables we employ the CV procedure.

Columns 5 and 6 of Table IV present the preliminary step estimates in which the two endogenous explanatory variables—annual total income and non-real estate assets—are regressed against the appropriate explanatory variables. To maintain consistency with the approach employed in estimating the selection equation we use the complete vector of covariates with the exception of real estate assets, which we exclude owing to its possible simultaneity to annual total income and non-real estate assets as we employ it as a measure of wealth. The estimation results suggest that demographic characteristics are important. Education, gender, age, employment and area income are statistically significant for annual income (column 5). Education, gender, area income and other regional controls are significant for non-real estate assets (column 6).

The identification of the model again requires identification variables. For the annual income equation (column 5) banks at the municipality level are statistically significant, but the remaining credit access variables are not. For the non-real estate assets equation (column 6) the retail stores availability measures are statistically significant. While these results suggest our access measures are identifying the model, some of the four additional identifying variables capturing the ownership and value of pension funds, current account ownership and the use of telebanking also appear to be important determinants of annual total income and non-real estate assets. To implement the Das *et al.* estimator we take the predicted propensity scores from equations (1) and (2), denoted $p_{Ni} = X_{Ni}\widehat{\beta}_N$ and $p_{Bi} = X_{Bi}\widehat{\beta}_B$, and estimate

$$D_i = X_{Di}\beta_D + \sum_{j=1}^{J} \alpha_1^j I_i^j + \sum_{k=1}^{K} \alpha_2^k A_i^k + h(p_{Ni}, p_{Bi}, r_{Ii}, r_{Ai}) + u_i \tag{5}$$

[12] We use the same (CV) criterion as in Das *et al.* (2003) The CV criterion is the sum of squares of forecast errors, where all the other observations are used to predict each single observation.

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where $h(\cdot)$ is a function capturing the inclusion of all its arguments, their higher orders and their corresponding cross-products. Our preferred model is that which minimizes our CV criterion. This requires estimating a very large number of models.[13]

Summarizing our preferred specifications for consumer debt, mortgage debt and total debt, respectively, we have the following. For consumer debt there is strong evidence of endogeneity, selection and nonlinearities in the endogenous explanatory variables. In contrast, the preferred model for mortgage debt suggests endogeneity only for non-real assets and the presence of selection bias. The result regarding the endogeneity of income-to-mortgage debt suggests that unobservable household characteristics determining income are generally irrelevant for access to mortgage credit as mortgage credit is widely available under subsidized schemes for low-income households. The preferred model for 'total debt' reinforces the evidence regarding endogeneity, selection and nonlinearities. The fact that this conclusion is similar to the consumer debt might reflect that 56% hold consumer debt and only 21% hold mortgage debt. Summarizing, the cross-validation criteria support the existence of selection, endogeneity and nonlinearities in the debt equations and highlight the value of the semiparametric procedure. The differences across debt type highlight the need to estimate separate models.

The first column of Table VI reports, for comparison sake, the ordinary least squares estimates for consumer debt from estimating equation (3), ignoring the potential presence of selection bias or endogeneity. The second column provides the parametric selection bias adjusted estimates based on Cox and Jappelli (1993), in which equations (1) and (2) are each estimated by probit and their respective inverse Mills ratios are included as additional regressors. These additional regressors are denoted IMR_N and IMR_B, noting that we also estimated a model, shown in column 3, which included interactions of these terms. Column 4 reports the preferred semiparametric estimates. The corresponding estimates for mortgage and total debt are shown in Tables VII and VIII respectively.[14]

Focus first on consumer debt demand. The estimates for the parametric model in column 2 in Table VI do not provide any evidence of selection bias, in contrast to the parametric model with the interactive term in column 3. However, the bias is small. The semiparametric model in column 4, in contrast, provides evidence of both forms of selection bias. There is also evidence of endogeneity of income and non-real estate assets.

On the basis of our CV investigation, which indicates that the estimates from the semiparametric procedure are preferred, we restrict our focus to the model in column 4 in Table VI. A number of important features are worth noting. First, as expected, there is a positive and statistically significant impact of income on consumer debt demand. Second, there is a concave relationship between the age of household head and the level of household debt. Third, the statistically significant coefficients on the residuals support the presence of endogeneity.

Focus on the results for mortgage debt demand in Table VII. While the parametric models do not find any evidence of selection bias, this is not the case for our preferred semiparametric model. However, the evidence supporting selection bias in the semiparametric model is rather weak. This is an interesting finding, since selection bias was detected in the consumer debt equation. Note that the questions in the survey to determine who is credit constrained (and/or discouraged) might be thought as more

[13] The scheme used in order to choose the preferred polynomial follows Table V. The overall setting implies defining the order of the polynomial and then estimating a model for all the possible combinations of the polynomial terms involved. For example, we defined set 1 including Income (I) and non-real estate assets (A) up to cubic terms, and the four residuals including only linear terms, so that we have 10 variables to combine, and then choosing the best model. We then defined set 2 including only linear terms, plus first-order interactions, so that we have 12 terms to combine. Then, we defined sets 3 and 4 including fixed linear terms, and varying second-order and third-order terms for I, and third-order terms for A, plus the linear terms for the four residuals and linear interactions, so that we had 13 terms to combine for each of them. We did this up to third-order polynomial for all the variables, including second-order interactions.

[14] All estimation results report bootstrap standard errors computed with 2000 replications.

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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.

Table VI. Estimation results of borrowing demand: consumer debt

Depvar: ln(consumer debt)	(1) No correction	(2) Parametric Correction 1	(3) Parametric Correction 2	(4) Semiparametric Correction
Income	0.0312***	0.0266***	0.0266***	0.0489***
	(0.00421)	(0.00155)	(0.00102)	(0.00237)
Income^2	−0.000147***	−0.000127***	−0.000127***	−8.81e−05***
	(2.33e−05)	(1.34e−05)	(1.02e−05)	(2.92e−05)
Income^3	1.71e−07***	1.49e−07***	1.48e−07***	1.07e−07***
	(2.99e−08)	(2.46e−08)	(2.47e−08)	(3.85e−08)
Non-real estate assets	−0.000692	−0.000816***	−0.000821	−0.0135***
	(0.00114)	(0.000138)	(0.000604)	(0.00159)
Real estate assets	0.000253**	−3.78e−05	−0.000139	3.14e−05
	(0.000117)	(5.53e−05)	(0.000247)	(0.000301)
Age	0.0657***	0.0452	0.0451***	0.0319**
	(0.0135)	(0.0314)	(0.0104)	(0.0153)
Age^2	−0.000700***	−0.000464	−0.000465***	−0.000421***
	(0.000131)	(0.000291)	(8.45e−05)	(0.000114)
Years of education	0.0393***	0.0288***	0.0277***	−0.0114
	(0.0129)	(0.000704)	(0.00158)	(0.0118)
Spouse present = 1	0.112	0.0636	0.0615	0.0678
	(0.212)	(0.139)	(0.132)	(0.251)
Male = 1	0.236*	0.195***	0.195	0.146***
	(0.136)	(0.0177)	(0.132)	(0.00206)
No. of persons in household	0.0371***	0.0479*	0.0509	0.00616***
	(0.00668)	(0.0257)	(0.0368)	(0.00206)
No. of employed persons in household	0.104***	0.0900*	0.0901***	−0.0108
	(0.00349)	(0.0529)	(0.0337)	(0.0782)
Unemployed = 1	−0.359***	−0.343	−0.355	−0.337
	(0.0841)	(0.288)	(0.391)	(0.297)
Signed job contract	−0.0675	−0.277	−0.290***	−0.188**
	(0.142)	(0.239)	(0.0721)	(0.0957)
Self-employed	−0.0176**	0.0573	0.0642***	0.0255
	(0.00874)	(0.143)	(0.0133)	(0.0628)
Area income	0.00613***	0.00407**	0.00378	−0.00717***
	(0.00191)	(0.00195)	(0.00255)	(0.000118)
North (1)	0.174***	−0.0778***	−0.0823	0.169***
	(0.0238)	(0.0214)	(0.223)	(0.0369)
Center (1)	0.0112	−0.223	−0.237*	−0.0158
	(0.0510)	(0.247)	(0.143)	(0.153)
South (1)	0.0769	−0.0779	−0.0828	−0.0899***
	(0.0704)	(0.113)	(0.134)	(0.0228)
Self-perception: financial service high	0.613***	0.958***	0.990***	0.993***
	(0.0319)	(0.152)	(0.0882)	(0.109)
Had delayed payments in past 12 months	0.0282	−0.162	−0.168*	0.147***
	(0.0678)	(0.158)	(0.0980)	(0.0239)
No. of arrears in past 12 months	0.0168***	0.00908	0.00277	0.113***
	(0.000242)	(0.0396)	(0.00191)	(0.00591)
No. of formal arrears in past 12 months	0.00427	0.0871	0.0827***	0.0838***
	(0.00996)	(0.0767)	(0.0217)	(0.00389)
No. of checks rejected to pay in past 12 months	0.0474	0.0582***	0.0555**	0.0572***
	(0.0549)	(0.0170)	(0.0219)	(0.00551)

Table VI. Continued

Depvar: ln(consumer debt)	(1) No correction	(2) Parametric Correction 1	(3) Parametric Correction 2	(4) Semiparametric Correction
$\mathrm{IMR}_B{}^C$		−4.212***	0.141	
		(0.183)	(1.529)	
IMR_N		−9.149***	−4.431**	
		(2.344)	(1.898)	
$\mathrm{IMR}_B{}^C * \mathrm{IMR}_N$			−12.86***	
			(4.415)	
r_I				−0.0313***
				(0.00684)
r_A				0.0123***
				(0.00408)
p_N^2				20.00***
				(2.120)
p_N^3				−14.58***
				(1.594)
p_B				0.705***
				(0.0391)
Constant	−3.616***	2.455	0.895	−7.619***
	(0.347)	(1.757)	(1.154)	(1.324)
Observations	1717	1717	1717	1717
R^2	0.224	0.242	0.242	0.265

Note: Bootstrap standard errors in parentheses. $***p < 0.01$; $**p < 0.05$; $*p < 0.1$. (1) Metropolitan region excluded. $p_N = X_N\widehat{\beta}_N = p$-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; $\mathrm{IMR}_B{}^C$ = inverse Mill ratio of positive consumer debt; IMR_N = inverse Mill ratio of unconstrained.

relevant to consumption loans rather than mortgages.[15] Also note that there is evidence supporting the endogeneity of non-real estate assets but not the endogeneity of income.

Two features of the Chilean financial system may be relevant in understanding these contrasting results across debt type. First, non-mortgage credit is restricted in access through banks, and ‘almost’ unrestricted through department stores cards. However, the amounts that can be borrowed in the latter are much smaller, and the interest rates much higher. Second, mortgage credit could be thought as almost unrestricted in access. That is, it is rare for institutions to refuse mortgage credit for a given property. The ‘only restriction’ commonly used by banks is that monthly payment cannot be larger than a quarter of monthly household income that the applicant is able to demonstrate. Income and age then determine the horizon of the mortgage, noting that mortgage credits are generally issued at 20 or 30 years. About 10% of current mortgages are obtained through government institutions with significant subsidies. Of the remaining households with mortgages, 30% of them are held through the state-owned bank ‘Banco Estado’. Most of these loans are associated with some sort of subsidy and/or facilitated access. However, richer households can obtain relatively lower interest rates in commercial banks. For example, they face a real interest rate of 4–5%, compared to about 6–7% for lower-income people for this period.[16]

Despite the lack of evidence of selectivity bias, there are substantial differences between the coefficients of the uncorrected and the semiparametric corrected model in column 4 of Table VII. This

[15] Note that questions are very similar to those in the Survey of Consumer Finances to determine credit constraints, as discussed above.

[16] Unfortunately, we do not have reliable data on interest rates for each corresponding loan in the survey.

Table VII. Estimation results of borrowing demand: mortgage debt

Depvar: ln(mortgage debt)	(1) No correction	(2) Parametric Correction 1	(3) Parametric Correction 2	(4) Semiparametric Correction
Income	0.0261*** (0.00321)	0.0230*** (0.00366)	0.0229*** (0.000375)	0.0263*** (0.00756)
Income^2	−0.000127*** (5.79e−06)	−0.000112*** (1.62e−05)	−0.000112*** (1.35e−06)	−0.000126*** (1.05e−05)
Income^3	1.40e−07*** (4.45e−09)	1.21e−07*** (4.19e−08)	1.21e−07*** (7.77e−10)	1.37e−07*** (4.47e−09)
Non-real estate assets	0.000520 (0.000751)	0.000424 (0.00160)	0.000432 (0.00132)	0.00221 (0.00315)
Real estate assets	0.000206 (0.000209)	−0.000375 (0.000437)	−0.000326 (0.000207)	0.000327 (0.000298)
Age	0.0684 (0.0767)	0.0483 (0.0876)	0.0501 (0.0310)	0.0559* (0.0305)
Age^2	−0.00117 (0.000970)	−0.000956 (0.00101)	−0.000977*** (0.000372)	−0.00103*** (0.000292)
Years of education	−0.00316 (0.0102)	−0.0200 (0.0289)	−0.0194 (0.0301)	−0.00632 (0.0107)
Spouse present = 1	−0.0385 (0.0239)	−0.147 (0.110)	−0.141 (0.286)	−0.0223 (0.0442)
Male = 1	−0.0162 (0.0711)	0.0343 (0.212)	0.0329 (0.0249)	−0.0570*** (0.00971)
No. of persons in household	−0.0311 (0.0832)	−0.00493 (0.00484)	−0.00493 (0.162)	−0.0201 (0.0541)
No. of employed persons in household	−0.113 (0.191)	−0.0772*** (0.0177)	−0.0770 (0.0859)	−0.113 (0.117)
Unemployed = 1	0.378 (0.729)	0.369 (0.305)	0.359 (0.845)	0.512 (0.798)
Signed job contract	0.144 (0.255)	0.0223 (0.421)	0.0268 (0.285)	0.188 (0.196)
Self-employed	−0.129 (0.417)	−0.126 (0.163)	−0.123* (0.0734)	−0.121 (0.138)
Area income	0.000669 (0.00567)	−0.00357 (0.00692)	−0.00339 (0.00761)	−0.000776 (0.00789)
North (1)	−1.025*** (0.113)	−1.049*** (0.0251)	−1.050*** (0.229)	−0.977** (0.405)
Center (1)	−0.239*** (0.00826)	−0.413*** (0.0468)	−0.408** (0.159)	−0.261 (0.338)
South (1)	−0.305 (0.360)	−0.359 (0.277)	−0.360 (0.708)	−0.289 (0.509)
Self-perception: financial service high	0.374 (0.229)	0.691** (0.313)	0.682*** (0.153)	0.406*** (0.0838)
Had delayed payments in past 12 months	−0.384 (0.573)	−0.152 (0.475)	−0.152 (0.136)	−0.288 (0.398)
No. of arrears in past 12 months	0.141*** (0.0135)	0.142*** (0.0258)	0.138 (0.118)	0.168*** (0.0499)
No. of formal arrears in past 12 months	−0.00707 (0.182)	0.0583*** (0.00551)	0.0578 (0.0611)	−0.0167 (0.0727)
No. of checks rejected to pay in past 12 months	−0.0911 (0.179)	−0.0832*** (0.00403)	−0.0846 (0.0951)	−0.0819 (0.0564)
$\text{IMR}_B{}^M$		−1.669 (1.256)	0.381 (1.710)	

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Table VII. Continued

Depvar: ln(mortgage debt)	(1) No correction	(2) Parametric Correction 1	(3) Parametric Correction 2	(4) Semiparametric Correction
IMR_N		−8.279 (9.649)	−4.487 (3.516)	
$\text{IMR}_B{}^M * \text{IMR}_N$			−5.808 (9.815)	
r_A				0.0453*** (0.0143)
$r_A * p_N$				−0.0756* (0.0396)
$r_A * p_B$				0.0396 (0.0317)
Constant	0.817 (1.179)	5.595* (2.997)	4.197*** (0.0432)	1.028 (1.033)
Observations	665	665	665	665
R^2	0.147	0.152	0.152	0.164

Note: Bootstrap standard errors in parentheses. *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$. (1) Metropolitan region excluded. $p_N = X_N \widehat{\beta}_N = p$-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; $\text{IMR}_B{}^M$ = inverse Mill ratio of positive mortgage debt; IMR_N = inverse Mill ratio of unconstrained.

reflects the impact of correcting for the endogeneity of income. Income and age display the expected profiles. While education has no statistically significant impact, gender of the household head becomes significant in the corrected model. This may reflect that income captures the relevant information for the banks when issuing mortgages, as discussed above. Other household characteristics do not have statistically significant coefficients.

Finally, consider the analysis of total debt demand in Table VIII, noting that the differences above in the processes determining mortgage and consumer debt suggests combining them is not appropriate. We report the estimates for the sake of comparison with studies which examine aggregate debt. The parametric estimates provide support for both sources of selection. Our preferred semiparametric specification confirms the role for both forms of selection, in addition to providing evidence of the endogeneity of income and non-real estate assets. In terms of bias correction, the results are similar to those for consumer debt.

Using our estimates we highlight some relationships which are useful in anticipating how credit demand might respond to changes in the Chilean economy resulting from income growth and an aging population. We derive the implicit elasticities of debt demand with respect to income and age. The profiles of the relationship of debt to income and age are shown in Figures 2 and 3 respectively for different types of debt. Those figures also show the corresponding derivatives. For comparison, estimates are also shown for the model with no correction terms, with the parametric correction terms and with the semiparametric correction terms respectively.

The first remarkable result is the degree of nonlinearity in these relationships. Both the debt/income and debt/age relationships exhibit concave profiles. Secondly, the parametric model is very similar to the uncorrected model, particularly in the case of consumer debt and total debt. However, the semiparametric model produces substantially different profiles. For the debt/income relationship, the derivative is underestimated by the uncorrected model and the model with the parametric correction terms. For the debt/age relationship, the derivative is overestimated by the uncorrected model and the parametric adjusted model. This is particularly true for younger household heads.

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Table VIII. Estimation results of borrowing demand: total debt

Depvar: ln(mortgage debt)	(1) No correction	(2) Parametric Correction 1	(3) Parametric Correction 2	(4) Semiparametric Correction
Income	0.0423*** (0.00333)	0.0375*** (0.00465)	0.0374*** (0.00371)	0.0630*** (0.00475)
Income^2	−0.000203*** (1.47e−05)	−0.000180*** (3.41e−05)	−0.000179*** (2.55e−05)	−0.000247*** (3.08e−05)
Income^3	2.39e−07*** (1.61e−08)	2.13e−07*** (4.49e−08)	2.11e−07*** (3.87e−08)	3.97e−07** (1.58e−07)
Non-real estate assets	−0.000364 (0.000397)	−0.000570 (0.000678)	−0.000552* (0.000323)	−0.00860*** (0.000844)
Real estate assets	0.000552 (0.000406)	−9.72e−05 (0.000452)	−0.000140 (0.000152)	0.000250 (0.000352)
Age	0.107*** (0.0144)	0.0761*** (0.0145)	0.0760*** (0.00677)	0.0739*** (0.0169)
Age^2	−0.00125*** (0.000175)	−0.000907*** (0.000155)	−0.000907*** (0.000135)	−0.000979*** (0.000190)
Years of education	0.0474*** (0.00774)	0.0322*** (0.00303)	0.0312*** (0.00405)	−0.00571*** (0.00195)
Spouse present = 1	0.288*** (0.0786)	0.187*** (0.00244)	0.184 (0.166)	0.194*** (0.0321)
Male = 1	0.0653 (0.113)	0.0824*** (0.00644)	0.0837** (0.0361)	0.0103 (0.0742)
No. of persons in household	−0.00965 (0.0184)	0.00633 (0.0112)	0.00915*** (0.000868)	−0.0335 (0.0208)
No. of employed persons in household	−0.0119 (0.0492)	−0.0112 (0.00967)	−0.0102 (0.0680)	−0.111*** (0.0221)
Unemployed = 1	0.0252 (0.0334)	0.108 (0.527)	0.0983 (0.246)	0.0590 (0.0467)
Signed job contract	0.0258*** (0.00176)	−0.201** (0.0843)	−0.209 (0.205)	−0.112 (0.140)
Self-employed	−0.00197 (0.0736)	0.0665 (0.0949)	0.0725* (0.0432)	0.0581*** (0.00326)
Area income	0.00766*** (0.00127)	0.00347*** (0.000535)	0.00326 (0.00287)	−0.00599* (0.00323)
North (1)	−0.121 (0.107)	−0.351*** (0.0834)	−0.351*** (0.0103)	−0.179 (0.136)
Center (1)	−0.0973*** (0.0112)	−0.359*** (0.0558)	−0.368*** (0.00948)	−0.186*** (0.0162)
South (1)	−0.137 (0.0968)	−0.275*** (0.0301)	−0.278** (0.121)	−0.303*** (0.0188)
Self-perception: financial service high	0.449*** (0.0541)	0.930*** (0.0313)	0.960*** (0.0254)	0.879*** (0.188)
Had delayed payments in past 12 months	−0.0259 (0.348)	−0.0733** (0.0322)	−0.0829 (0.258)	0.120*** (0.0101)
No. of arrears in past 12 months	0.0151*** (0.00112)	0.0206*** (0.00790)	0.0153 (0.0112)	0.101*** (0.0282)
No. of formal arrears in past 12 months	0.00578 (0.0226)	0.103*** (0.00563)	0.0972*** (0.00370)	0.0879 (0.0536)
No. of checks rejected to pay in past 12 months	0.0306 (0.0487)	0.0458 (0.0600)	0.0413 (0.0990)	0.0356 (0.0448)
$\text{IMR}_B{}^A$		−4.199*** (0.566)	0.849 (0.918)	

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Table VIII. Continued

Depvar: ln(mortgage debt)	(1) No correction	(2) Parametric Correction 1	(3) Parametric Correction 2	(4) Semiparametric Correction
IMR_N		−11.43***	−6.021***	
		(4.029)	(2.244)	
${IMR_B}^A * IMR_N$			−14.80***	
			(0.598)	
r_I				−0.0250***
				(0.00462)
r_I^2				7.46e−05***
				(5.41e−06)
r_I^3				−2.46e−07
				(1.66e−07)
r_A				0.00774***
				(0.000769)
p_N^2				19.56
				(13.25)
p_N^3				−13.88
				(10.45)
p_B^3				0.678***
				(0.0730)
Constant	−3.587***	3.420	1.598***	−7.552**
	(0.524)	(2.107)	(0.198)	(3.412)
Observations	1947	1947	1947	1947
R^2	0.290	0.305	0.305	0.328

Note:Bootstrap standard errors in parentheses. $^{***}p < 0.01$; **p<0.05; *p<0.1. (1) Metropolitan region excluded. $p_N = X_N \widehat{\beta}_N = p$-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; ${IMR_B}^A$ = inverse Mill ratio of positive total debt; IMR_N = inverse Mill ratio of unconstrained.

Although the income and age profiles are interesting, it is more insightful to consider the weighted average derivatives, as these incorporate the income and age distribution of the sample. In the uncorrected model the consumer debt-to-income weighted average derivative is estimated at 2.4% with a standard deviation (SD) of 0.3% (see Table IX). As debt is in logarithms and income is in thousands of US dollars, the coefficient is a semi-elasticity. This indicates that a US $1000 increase in annual income would produce an increase of 2.4% in consumer debt. The preferred semiparametric model produces a semi-elasticity of 4.4% with a 0.7% SD (see columns 1 and 2 in Table IX). As annual average total household income is about US $33,100 in the corresponding subsample, a US $1000 increase represents 3.3% of annual income. This generates an elasticity of 1.47 (compared to 0.78 in the uncorrected model and 0.66 in the model with parametric correction). These results of elasticity imply a very strong response to income.

The mortgage debt-to-income weighted average derivative is estimated to be 1.5% with an SD of 0.4% in the uncorrected model, whereas in the semiparametric model it is 1.6% with a 0.4% SD (Table VIII). As annual average household income is about US $56,500 in the corresponding subsample, this produces an elasticity of 0.88 (compared to 0.86 and 0.76 in the uncorrected and parametric models respectively). As with consumer debt, the response of mortgage debt to income is very strong. As noted above, as higher-income households can access lower interest rates, it could be argued that the response to income could include a response to the interest rate. Although we cannot sepa-

Table IX. Weighted average derivatives

	Income		Age		Average	Average
	Weighted average derivative	Bootstrap standard error	Weighted average derivative	Bootstrap standard error	income (US $ thousands)	age
Consumer debt						
No correction	0.02351	0.00279	−0.00154	0.00318	33.1	48.0
Parametric correction	0.01994	0.00276	0.00060	0.00340		
Semiparametric correction	0.04433	0.00689	−0.00854	0.00381		
Mortgage debt						
No correction	0.01527	0.00354	−0.03787	0.00791	56.5	45.5
Parametric correction	0.01337	0.00414	−0.03876	0.00815		
Semiparametric correction	0.01551	0.00393	−0.03750	0.00795		
Total debt						
No correction	0.03103	0.00290	−0.01310	0.00358	35.2	47.9
Parametric correction	0.02746	0.00288	−0.01070	0.00382		
Semiparametric correction	0.05069	0.00721	−0.01987	0.00407		

rate those effects, this observation would support the relevance of investigating the role of income in credit demand.

Finally, the total debt-to-income weighted average derivative is estimated to be 5.1% with a 0.7% SD in our preferred model. Since annual average household income is about US $35,200 in this appropriate subsample, the total debt-to-income elasticity is estimated at 1.78. This contrasts with the estimates of 1.09 and 0.97 in the models without the correction terms and with the parametric correction terms respectively. Note that the substantial differences in the estimated elasticities reinforce the importance of the semiparametric corrections. The elasticities are much larger in the semiparametric models.

The evidence here clearly supports a very strong and positive response in the demand for debt from changes in household income. While this result seems reasonable, it contrasts with much of the existing evidence for other economies, which indicates substantial variability in the estimate of the income effect. In fact, there is even dispute with respect to the sign of the effect (see Crook, 2006), noting that most studies consider total debt. While a positive nonlinear effect of income is found for the USA, studies do not agree regarding the sign of the effect for Italy. Our results provide clear evidence of a positive relationship between income and debt.

The results related to the life cycle behavior of credit demand are also particularly interesting for an economy with an aging process. The consumer debt-to-age weighted average derivative is estimated to be −0.9% with a 0.4% SD in our preferred model, compared to an unadjusted estimate of −0.15% with an SD of 0.3%. Average age is about 48 years in the subsample of households who hold consumer debt. The mortgage debt-to-age weighted average derivative from our preferred specification is estimated to be −3.75% with a 0.8% SD—almost identical to the unadjusted estimation (−3.79 with an SD of 0.7%). Average age is about 45 years in the corresponding subsample. Total debt-to-age weighted average derivative is estimated to be −1.98% with a 0.4% SD, with the unadjusted counterpart being −1.3% (SD 0.35%).

This substantial difference in estimated elasticities highlights the importance of our approach. The smallest differences occur for mortgage debt to age, but the figures reflect this because the average age is very close to the point where the derivatives from the different models cross each other. At lower and higher ages the differences in the derivatives are much larger. Evidence from the USA and Italy show a life cycle humped age profile and this is similar to what we find for Chile for consumer credit and total debt. However, mortgage credit seems to exhibit a decreasing profile, indicating that Chilean individuals may face a different life cycle process for mortgage debt.

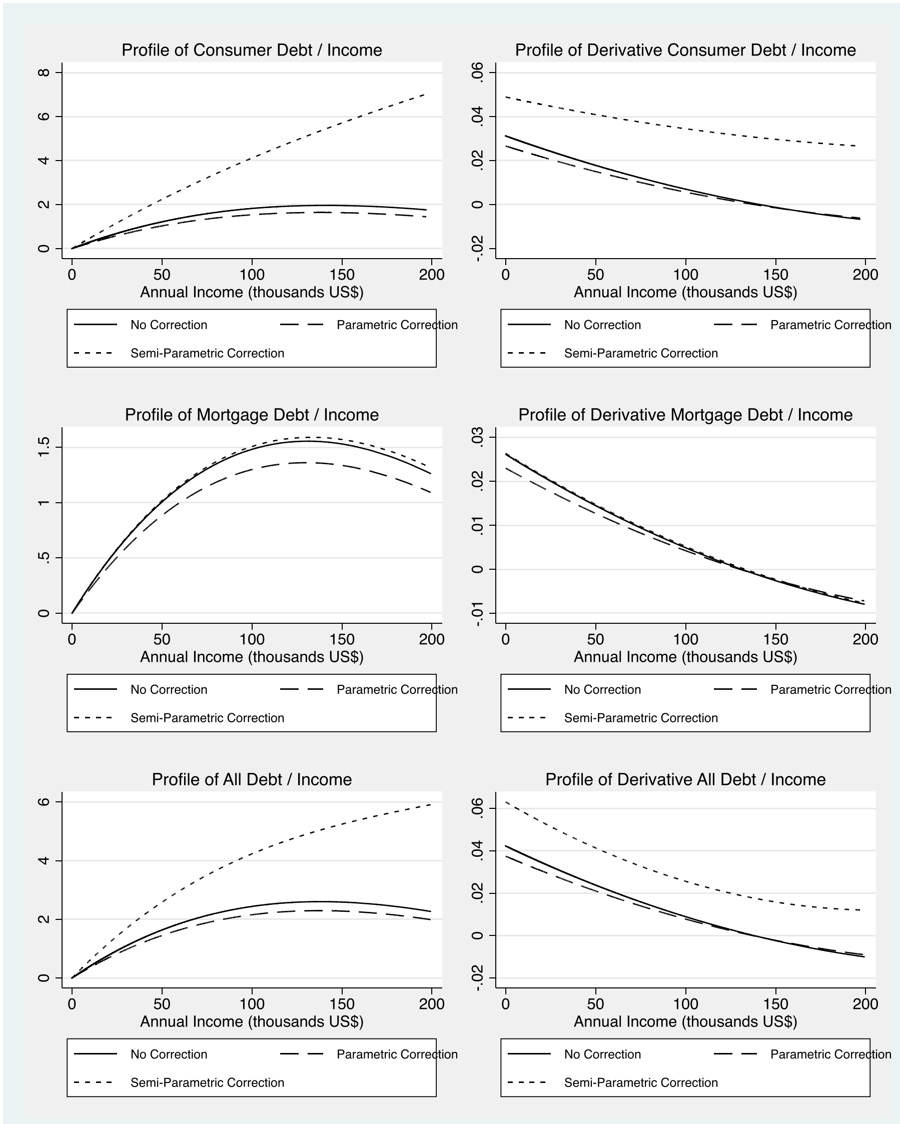

Figure 2. Estimated profile debt/income. Debt/income profiles are (left) relationship $= \alpha_1^1 I_i + \alpha_1^2 I_i^2 + \alpha_1^3 I_i^3$; (right) derivative $= \alpha_1^1 + 2\alpha_1^2 I_i + 3\alpha_1^3 I_i^2$

Finally, consider the implication of our results for the changes in debt level that might be anticipated for the Chilean economy if the credit system remains unchanged but there are changes with respect to age composition of the population and increases in household income levels. Since debt levels are a stock and income is a flow, we interpret the results using the underlying assumption that annual income proxies permanent income in terms of determining households' behavior, and that there is parameter stability as economy growths. Our results suggest that elasticities and semi-elasticities would increase significantly. As an example, total household income in Chile has increased 2% per year during the past decade. In the same period, the aging process has implied an increase of average age of household

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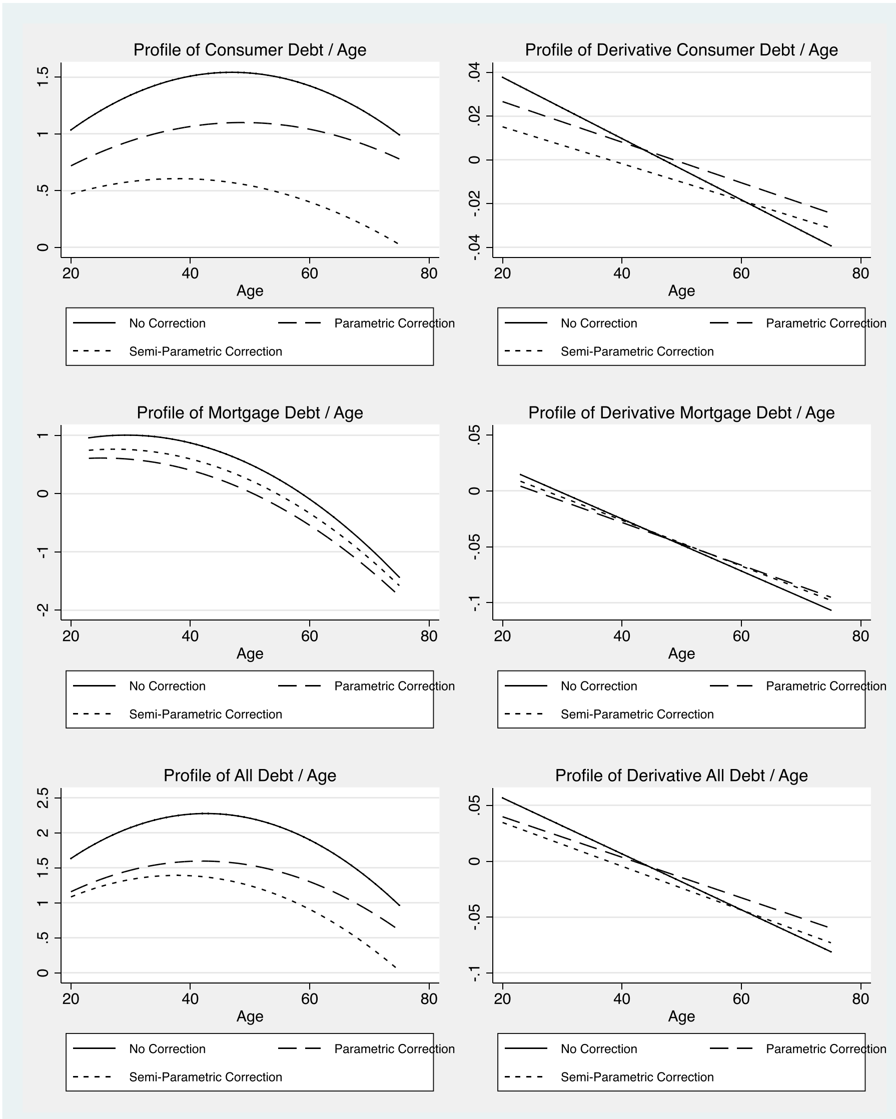

Figure 3. Estimated profile debt/age. Debt/age profiles are (left) relationship $= \beta^{\text{Age}}\text{Age}_i + \beta^{\text{Age}^2}\text{Age}_i^2$; (right) derivative $= \beta^{\text{Age}} + 2\beta^{\text{Age}^2}\text{Age}_i$

heads of 1 year in every 3 years.[17] Using these figures, in 3 years' time debt-to-income elasticities would increase from 1.47 to 1.55 in the case of consumer debt, from 0.88 to 0.90 in the case of mortgage debt, and from 1.78 to 1.88 in the case of total debt. Elasticities are expected to increase significantly as income increases due to the nonlinear behavior of debt demand. As elasticities become larger than 1, developing economies may experience a debt growth which is larger than income growth. This effect is likely to be larger for consumer debt. Certainly, the fact that households access and take

[17] Own calculations using the households' National Survey for Socioeconomic Characterization (Encuesta de Caracterizacion Socioeconomica Nacional—CASEN), 1990–2009.

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on more debt can be interpreted as beneficial for individual consumers. However, it also has important implications for financial stability. Our results imply that credit growth would be led by consumer debt, increasing overall debt-to-income ratios. Larger level of debt might make households more vulnerable to financial distress, implying a greater need for monitoring household default behavior.

Similarly, the aging process emphasizes the buffering role of age. The aging process in Chile indicates that in a 3-year period with a population 1 year older on average, the semi-elasticity of consumer debt to age would go from -0.8% to -0.9%, that of mortgage debt to age from -3.8% to -4.0%, and that of total debt to age from -1.9% to -2.2%. These results suggest that the nonlinear feature of credit demand to age would produce a larger diminishing effect on debt. The level at which this aging effect could compensate the increase of debt because of income growth is an empirical question that requires more research.

5. CONCLUSIONS

This paper represents the first attempt to investigate the determinants of the demand for credit in a developing economy by examining novel Chilean data to explore the relationship of borrowing constraints on credit demand. The evidence suggests that there is an underlying selection process, based on unobservables, for consumer debt models which subsequently influences the level of demand. In contrast, there appears to be no such systematic role for unobservables for mortgage debt. While for consumer loans there is evidence that income and non-real estate assets are endogenous, for mortgage debt there is only support for the endogeneity of non-real estate assets.

We estimate the elasticity of consumer debt to income, measured as the weighted average derivative, to be 1.47 for consumer debt, 0.88 for mortgage debt and 1.78 for total debt. This suggests that relaxing borrowing constraints is likely to increase borrowing of low-income households. As low-income households take on debt, the nature of the debt-to-income relationship will change. The results also indicate than the aging process common in developing economies will have a moderating effect on the demand of debt, particularly with respect to mortgage debt. Developing countries experiencing a rapid income growth jointly with a deepening financial process may follow a similar pattern. That is the case for countries such as Peru and Colombia in Latin America, where the economic and financial developing process has been following the Chilean experience with approximately a 10-year lag.

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REFERENCES

Banco Central de Chile. 2009. *Encuesta Financiera de Hogares: EFH 2007 Metodología y Principales Resultados*. Banco Central de Chile: Santiago.

Bertaut CC, Haliassos M. 2005. *Credit cards: facts and theories. CFS working paper series 2006/19*. (CFS): Frankfurt.

Cox D, Jappelli T. 1993. The effect of borrowing constraints on consumer liabilities. *Journal of Money, Credit and Banking* **25**(2): 197–213.

Crook J. 2006. Household debt demand and supply: a cross-country comparison. In *The Economics of Consumer Credit*, Bertola G, Disney R, Grant C (eds). MIT Press: Cambridge, MA; 63–92.

Crook J, Hochguertel S. 2007. US and European debt and credit constraints: comparative micro evidence from the last 15 years, Tinbergen Institute Discussion Paper TI 2007-087/3.
Das M, Newey W, Vella F. 2003. Nonparametric estimation of sample selection models. *Review of Economic Studies* **70**(1): 33–58.
Djankov S, McLiesh C, Shleifer A. 2007. Private credit in 129 countries. *Journal of Financial Economics* **84**(2): 299–329.
Ferri G, Simon P. 2002. Constrained consumer lending: methods using the survey of consumer finance, *Working paper*, University of Bari.
Galetovic A, Poduje I, Sanhueza R. 2009. Malls en Santiago: de centros comerciales a centros urbanos. *Estudios Públicos* **114**: 219–252.
Grant C. 2007. Estimating credit constraints among US households. *Oxford Economic Papers* **59**(4): 583–605.
Gropp R, Scholtz JK, White MJ. 1997. Personal bankruptcy and credit supply and demand. *Quarterly Journal of Economics* **112**: 217–251.
Gross DB, Souleles NS. 2002. Do liquidity constraints and interest rates matter for consumer behavior? Evidence from credit card data. *Quarterly Journal of Economics* **117**(1): 149–185.
Jappelli T. 1990. Who is credit constrained in the U.S. economy. *Quarterly Journal of Economics* **105**(1): 219–234.
Jappelli T, Pischke JS, Souleles NS. 1998. Testing for liquidity constraints in Euler equations with complementary data sources. *Review of Economic and Statistics* **80**(2): 251–262.
Ruiz-Tagle J. 2009. Household credit constraints and the cost of credit, Working paper, Universidad de Chile.
Vella F. 1998. Estimating models with sample selection bias: a survey. *Journal of Human Resources* **33**(1): 127–169.
Zeldes S. 1989. Consumption and liquidity constraints: an empirical investigation. *Journal of Political Economy* **97**(2): 305–346.

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