dECON

Facultad de Ciencias Sociales
UNIVERSIDAD DE LA REPÚBLICA

Documentos de Trabajo

Household Debt: the Role of Income and Business Ownership in a Small Emerging Country

José Ignacio Rivero y Graciela Sanroman

Documento No. 08/20
Noviembre 2020

ISSN 0797-7484

Household debt: the role of income and business ownership in a small emerging country

José Ignacio Rivero* Graciela Sanroman†

November 25, 2020

We analyze the debt side of household balance sheets in a small economy with underdeveloped financial markets. Our main focus is on the influence of income on the intensive margin of debt holdings and how business ownership affects that relationship. Using data from a novel Uruguayan dataset, we estimate selection-corrected Conditional Quantile Regressions (CQR). The motivation for using CQR stems from the fact that the conditional distribution of debt holdings is highly asymmetric. This makes it worthwhile to take the analysis beyond the mean. In addition, understanding the effects of income and entrepreneurship for the most indebted households is a policy relevant question. We find that income does not affect the probability of being indebted but it has a significant impact on the intensive margin of debt holdings. The income elasticity of debt stocks is positive and varies substantially across types of households, being those who own formal businesses the most sensitive to income variations.

JEL Classification: C21, C24, D14, G0

Keywords: Household finance, Household debt, Conditional Quantile Regression

*THEMA-CY Cergy Paris Université. e-mail:jose-ignacio.rivero-wildemauwe@u-cergy.fr

†dECON-FCS-UdelaR. e-mail: graciela.sanroman@cienciassociales.edu.uy

Resumen

Analizamos los pasivos en los balances de los hogares en un país pequeño con mercados financieros muy poco desarrollados. Nuestro foco es en la influencia del ingreso en el márgen intensivo del endeudamiento, y en cómo afecta esta relación la propiedad de negocios. Usando datos recientemente disponibles para Uruguay estimamos Regresiones Cuantílicas Condicionales (RCC) corregidas por autoselección. La motivación para utilizar RCC surge del hecho de que la distribución del endeudamiento de los hogares es altamente asimétrico, lo cual justifica generalizar el análisis más allá de la media. Además, entender el efecto del ingreso según tipo de hogar para los hogares endeudados es una pregunta de intéres desde el punto de vista de la política económica. Encontramos que el ingreso no afecta la probabilidad de que un hogar esté endeudado pero que si tiene un efecto significativo en el márgen intensivo del endeudamiento. La elasticidad ingreso del stock de deuda es positivo y varia sustancialmente entre tipos de hogar, siendo aquellos que poseen negocios formales los que presentan mayor sensibilidad a las variaciones del ingreso.

JEL Classification: C21, C24, D14, G0

Keywords: Finanzas de los hogares, Deudas de los hogares, Regresiones Cuantilicas Condicionales

1 Introduction

The Great Recession of 2007-2009 constitutes one of our last reminders that studying household debt is an extremely policy-relevant pursuit. It has been thoroughly documented that larger increases in households' indebtedness during the years leading to the crisis were in turn associated with greater contractions in economic activity (Mian and Sufi (2010), Martin and Philippon (2017)). In fact, this is not exceptional of the 2007-2009 slump but rather, a feature of several recent recession episodes across the world (Mian and Sufi (2018)). In this context, understanding the determinants of household debt is of paramount importance.

Although the analysis of the debt side of household balance sheets is a very active area of research, it has been less studied than the assets side. Zinman (2015) provides a very good survey of recent findings and challenging puzzles related to households' behavior in the credit market. He highlights that observed decisions in this market have relevant implications beyond balance sheets. In particular, they can be helpful to develop and test intertemporal choice models, to determine the opportunity cost of consumption and investments, to develop contract theory interactions of consumers with firms and to provide helpful insights for the regulation of debt markets.

Household debt is particularly relevant in developing countries, such as those of Latin America, where equity markets are absent or very poorly developed. Ruiz-Tagle and Vella (2015) study the determinants of credit demand in Chile using a novel Chilean dataset. They focus on life-cycle effects and the income elasticity of demand for debt, taking into account the presence of borrowing constraints. They follow the Heckman selection model of Cox and Japelli (1993), with two equations for the selection (debts holders and constrained households) and one for the intensive margin, but in a more flexible semiparametric manner.

Regarding the link between households' balances and entrepreneurship, Heaton and Lucas (2000) have demonstrated that business ownership constitutes a major determinant of household demand for risky financial assets. Hurst and Lusardi (2004) analyze the relationship between wealth and entry into entrepreneurship. Fairlie and Krashinsky (2012) explore the issue of liquidity constraints for entrepreneurs. The interest of business ownership in the study of household demand for credit can be established from an empirical perspective but also from a theoretical point of view. This is because it is expected that the access of households to different segments of the credit market is heterogeneous, and also because the role of current income on decisions about consumption, savings and debts might substantially vary among those types of households.

The main goal of this paper is to analyze the major factors which influence the likelihood that a household is indebted (extensive margin) and households' debt amount (intensive margin). Our focus is on the influence of income in the intensive margin of debt holdings, and the role of business ownership into that relationship.

This work is closely related with Cox and Japelli (1993) and Ruiz-Tagle and Vella (2015), but we use a different dataset, we estimate a model for the actual level of debt instead of the desired demand, and we estimate quantile instead of mean regressions. Also, we specifically assess how entrepreneurship affects the influence of income on the debt level of households. Finally, we use data from a small developing country where mortgage and consumer markets are segmented and most private firms depend on credit to fund their business.

Given the asymmetric nature of the distribution of debts, quantile regression techniques seem especially well suited from a statistical perspective. Moreover, the quantile regression estimates are particularly appealing from a policy point of view, as the behavior of debts at the top of the distribution are of high interest to financial stability.

To estimate quantile regressions we follow the novel Arellano and Bonhomme (2016) method to correct quantile regression estimates for non-random sample selection. To our knowledge, this is the first time that quantile regressions corrected for self-selection are applied to the study of household debts.

We use data from the Survey of Uruguayan Household Finances (Encuesta Financiera de los Hogares Uruguayos-EFHU), collected during 2013-2014; which is very similar to that of Chile used by Ruiz-Tagle and Vella (2015). Chile and Uruguay are Latin American countries that share the language, are similar in terms of culture, and political and economic institutions. Also, both economies are usually ranked at the top of Latin America in many indicators such as GDP per capita or Human Development Index (HDI), while ranked at the bottom of others such as poverty rates (CEPAL). However, previous studies show that they differ greatly on income distribution. Uruguay is the country in which income is more equally distributed in Latin America, while Chile ranks in the middle (CEPAL). In addition, the magnitude and evolution of domestic debts of the private sector were quite different in the last decade.

Figure 1 shows that domestic credit to the private sector has been increasing in Chile since the nineties and it was around 110% of GDP by 2015. In contrast, this Figure shows that in Uruguay this ratio has been almost stable in the range 25%-35% since the beginning of the nineties (except for the period 1998-2003 when a financial crisis and a huge devaluation of the Uruguayan peso took place).

Those facts can be associated with the poor development and the limited competitive environment that characterize Uruguayan financial markets, in comparison with those of Chile. The Uruguayan financial markets are very shallow, there is a narrow segment of negotiable obligations and there is almost no equity market. Households' savings are in bank accounts and most firms depend exclusively on banks to cover their financial needs. Also, active interest rates are very high; in particular those nominated in Uruguayan pesos in the consumer segment were over 30% in recent years, while inflation was below 10% in the same period (Figure 2).

The contribution of this paper is twofold: Firstly, we estimate CQR for households' level of debt taking into account non-random selection through using Arellano and Bonhomme (2016)'s novel method, which is very suitable for the analysis of household debts. Secondly, we investigate how does business ownership affect households' liabilities.

We find that income is not significant to explain the probability of being indebted. Notice that such result does not conflict with the Permanent Income Hypothesis (PIH); because according with the PIH it is the relationship of current income with permanent income which determines the household's demand for credit. As expected, from the analysis of the intensive margin we find that selection-corrected Conditional Quantile Partial Effects (CQPEs) of income are positive and significant along the conditional distribution of debts, and vary a lot among type of households. Income elasticity of those households with formal businesses is the highest: at around 1, slightly decreasing along the distribution. On the other side, income elasticity for those with informal businesses is around 0.5 and almost constant over debts quantiles. Finally, income elasticity of employees goes from 0.65 at the bottom of the conditional distribution to zero at the top tail.

The paper is organized as follows. The next section describes the data and main facts. Section 3 presents the methods we use, in particular those related with the Arellano and Bonhomme (2016) estimator, following the description that the authors provide in their article. Section 4 presents and analyzes the main results. The final section includes some preliminary conclusions.

2 Data and main facts

We use data of "Encuesta Financiera de los Hogares Uruguayos" (EFHU), collected during 2013 and 2014. EFHU is a cross-sectional survey conducted by dECON-UDELAR and sponsored by the Banco Central del Uruguay and Ministerio de Economía. The EFHU is a sub sample of 3,490 Uruguayan households of the "Encuesta Continua de Hogares" (ECH) of "Instituto Nacional de Estadística" and it's representative at the national level.

EFHU collects information on household assets, liabilities, income, expenditure and socio-economic data on household members. The data is completed with stochastic multiple imputation to deal with the well known item non-response bias, an important characteristic in household financial surveys.

Table 1 shows statistics about households' assets and debts. Real estates account for 75% of households' assets. About 62% of Uruguayan households own their main residence. Housing is the asset that has the largest impact on household wealth (representing 55 per cent of total assets), and the median value of the main residence is 60,000 dollars. In adittion, 13% of Uruguayan households have other real estate properties, the median value of other real estate is 71,000 dollars and account for 23% of total assets. On the debt side, 8% of households have mortgage debts related to housing and 36.5% have consumer debt. However, the former represents half of households liabilities while the later represents around 38%. The conditional median value of total debts is 2,460, while this figure for mortgage debts and consumer debts are 13,608 and 3,816 respectively.

Table 2 replicates Table 1 of Ruiz-Tagle and Vella (2015), but includes an additional classification of households according to the employment status of household members. The data show that income and debts are less concentrated in Uruguay than in Chile. However, mortgage debt is more concentrated than income (like in Chile), while consumer debt is much less concentrated.

Almost half of Uruguayan' households have some debt (70% in the US) while only 2% have stocks or bonds. In Uruguay the credit market is more developed than the asset side of the financial market. There is no bankruptcy protection for people, but debt forgiveness was in the recent past a common practice in the case of debts created by unpaid taxes or related to payments to public firms that provide water, electricity or phone services. The fraction of households with checking accounts is very low (8% against 50% of saving accounts), thus bank overdrafts are not relevant. Concerning credit demand motives 37% consumer debt was generated to buy durable consumption (housing, vehicles, furniture), 10 per cent to refinance a previous debt, 30 per cent for non durable consumption, 6 per cent to face medical expenditures, and 6 per cent to fund trips and parties. Also, the proportion of indebted households is similar among income groups, but mortgage loans are more likely within high income households while consumer debts are less frequent. As expected, credit restrictions are negatively correlated with income.

The distribution of income is close to the distribution of households along ages, but 63% of total debts is held by households where the average age of adults is between 35 to 54 years old, and a similar figure is observed for mortgage debt. Concerning consumer debts, the share of medium age households is still large but lower, and old people increase their participation (12 per cent consumer debt versus 6 per cent mortgage debt). Participation rates in the credit market is hump-shaped over age, in particular in the mortgage segment. On the other hand, the proportion of households facing credit restrictions is decreasing in the mortgage and consumption segment, but this pattern is smoothed when considering both types of restrictions simultaneously.

Those with primary education represent 20% of Uruguayan households, but 10.6% of income and 5.7% of total debt. On the other side, those with tertiary education also represent 20% of the population but concentrate 36.7% of total income and 43.5% of total debts. That fact is completely driven by mortgage debts, as the share of households with tertiary education within the consumption credit segment is 22.6% (households with secondary school are the ones who concentrate most of this type of debt at 67.2%). The participation rate patterns change substantially among educational groups: 16.8% versus 2.7% respectively for tertiary and primary school in the mortgage segment; and 33.8% vs 39.9% in the consumer credit segment. Constrained households are much less frequent among highest educated group than among the other groups, however almost one over five households with highly educated members declares facing credit constrains.

About 10% of Uruguayan households own some formal business and an additional 10% run informal business, but income and debt shares of the former more than duplicates that of the later (income 16 versus 7.2; debt 18.6 versus 7.4). Employees (43% of Uruguayan households) and formal business owners behave similarly in terms of participation in mortgage credit, but the rate of participation in the consumer credit market is lower for households with formal firms. Also, the incidence of mortgage debt among employees and formal business owners doubles that of those with informal businesses. Employees account for 56% of the value of mortgage credits and households with formal business 25%. Consumer debts are less concentrated, but employees still own more than half of that type of credit.

Table 3 shows participation rates for several types of debts by three type of household: employees, households with informal business and households with formal business. About half of Uruguayan households hold debts. Among those, households with formal businesses exhibit the lowest proportion. Mortgage debts are less frequent among households with informal businesses, while consumer debts are less frequent among households with formal businesses. Debts with the government (taxes) and state-owned public utility companies are more frequent among households with informal business. Such a pattern can be interpreted as the effect of borrowing restrictions, given that the cost of credit is higher in the consumer segment than in the mortgage one. Also, debts with public institutions are created simply by avoiding the payment of taxes or services bills.

Tables 4 and 5 report statistics about the magnitude of liabilities. Conditional statistics are computed, using only those households that hold each type of debt. The levels of debts are quite large for households with formal businesses, due to the incidence of mortgage debts. On the other side, average debts with the government of informal business owners are 50%

higher than those of employees and households with formal businesses. The magnitude of debts of households with formal businesses is higher at every percentile of the conditional distribution, in particular from the median to the top that gap increases monotonically. Those facts are illustrated in Figure 3, that plots the unconditional percentiles of debts for the three types of households.

The ratio of debt to income of formal business is also higher (Table 5), in particular at the top of the distribution (at the percentile 90th is twice those of informal business). Finally, the ratio of debts with respect to assets is lower for those with formal business at every percentile, but particularly along the top half of the distribution. Employees exhibit the highest debt to asset ratios, followed by households with informal business. At the top of the distribution of that ratio figures are 3.3, 1.9 and 0.7; respectively for employees, informal business and formal business owners.

Figure 4 provides univariate kernel density estimates of income and debts (scaled by an inverse hyperbolic sine transformation) for indebted households, by type. The densities of both variables for households with formal businesses lie to the right of those for employees and informal business owners. Also, the variance of income and debt of formal entrepreneurs are higher than those of informal business, and these are greater than those of employees. Furthermore, Figure 4 also shows that the distribution of debts is highly asymmetric itself and also in comparison with the distribution of income.

Those facts highlight the suitability, from a statistical perspective, of using the quantile regression approach to study the behavior of households in the credit market. In addition, the quantile regression estimates are particularly appealing to study household debt, due to economic policy reasons, to the extent that the behavior of debts at the top of the distribution are of high interest to financial stability.

Finally, Figure 5 provides smoothed non-parametric estimates of the bivariate income-debts copula for indebted households by type[1]. Estimated copulas reveal a strong dependence between income and debts in the whole sample, for employees and, in particular for households

[1]We use the estimation procedure proposed by Deheuvels and Hominal (1979), that address the well known "boundary bias" of the non parametric kernel estimators for copulas using the "Mirror Image" technique, consisting of adding observations using the "reflection" principle.

with informal businesses. However, that dependence is weak for households with formal businesses. Those facts can be associated with the presence of borrowing restrictions, which are mitigated by the ownership of real estates that can be used as collateral, but strengthened by income risk. The heterogeneous pattern of the observed relationship between income and debts motivates to study how income elasticities vary between types of households. Furthermore, from a theoretical point of view there are at least two reasons behind that choice. First, it is expected that households with formal businesses can borrow both from the corporate and the household segment of the credit markets, while employees and informal business owners must borrow only from the latter. Second, and most important: the role of income on optimal decisions about consumption, savings and debts is likely to be very heterogeneous among those types of households.

3 Methodology

The main goal of this paper is to analyze the major factors that influence the likelihood that a household is indebted (extensive margin) and households' debt amount (intensive margin). More precisely, we focus on the influence of income in the intensive margin of debt stock, and the role of business ownership into that relationship.

Cox and Japelli (1993) propose a model to estimate household liabilities conditional on holding positive debt and being unconstrained in the credit market. They use a three equations model à la Heckman. Two selection equations are used in the first stage: having debts and not been constrained in the credit markets are the dependent variables of those two equations. The dependent variable of the equation of the intensive margin is the magnitude of debt for those household that are indebted and do not face borrowing restrictions.

Ruiz-Tagle and Vella (2015) estimate a similar model but they relax the distributional assumptions of the Heckman model. In addition, they address the issue of potential endogeneity of income. They estimate the model in a semiparametric manner using a control function approach, where correction factors are obtained from linear probability models for the two selection equations and a reduce form estimates for income.

The core of our empirical analysis is the estimation of conditional quantile regressions for the intensive margin of the level of debt. Notice that quantile regressions are particularly attractive for our goal, because of the asymmetric nature of the distribution of debts (see Figure 4). However, non-random selection is quite important for the demand for credit (Ruiz-Tagle and Vella (2015); Cox and Japelli (1993)), and thus some procedure to correct the estimates of the intensive margin is needed. In a recent article Arellano and Bonhomme (2016) propose a relatively simple method to correct quantile regression estimates for non-random sample selection. We use that approach to estimate the model.

The extensive margin is interesting in itself and also needed as a first stage of the Arellano and Bonhomme procedure. To analyze the extensive margin Probit models are estimated. In order to satisfy the exclusion restrictions two set of covariates are included: variables that would affect the extensive and the intensive margin and variables that affect only the extensive margin. Fortunately, the EFHU questionnaire includes some questions that can act as exclusion restrictions, as it is discussed in the next section.

The classic Heckman selection model is given by:

$$Y^* = X'\beta + \varepsilon \tag{1}$$

Y^* is observed when the binary selection indicator D is equal to one

$$D = \mathbf{1}(\eta \leq Z'\gamma) \tag{2}$$

where X is a subset of Z.

The scalar unobservable η is assumed independent of Z but possibly correlated with the error term ε.

Let us define $Y = DY^*$, $\mathbf{E}(Y^*|X)$ can not be estimated, but we can estimate:

$\mathbf{E}(Y^*|D = 1, Z) = \mathbf{E}(Y|D = 1, Z) = X'\beta + \mathbf{E}(\varepsilon|D = 1, Z) = X'\beta + \Lambda(Z).$

Where $\Lambda\left(Z\right)$ is a selection correction factor. This model can be estimated using a two-step estimator in Gaussian models as in Heckman (1979). But the method can be extended to allow for semi- or non- parametric specifications using the control function approach (like in Ruiz-Tagle and Vella (2015)), provided additivity of the latent model (1) in X and ε is maintained. However, non-additive models such as quantile models cannot be studied using those techniques.

The latent model in the quantile selection model of Arellano and Bonhomme (2016) is given by:

$$Y^* = X'\beta\left(U\right). \tag{3}$$

Under the assumption that $\beta\left(U\right)$ is increasing in u, U is uniformly distributed on (0,1) and independent of X.

The classical conditional quantile regression model is given by,

$$Q\left(\tau, X\right) = X'\beta\left(\tau\right).$$

Maintaining the other assumptions of the Heckman Gaussian model, Arellano and Bonhomme (2016) assume that (2) holds with a Gaussian η independent of Z, so that equivalently:

$$D = \mathbf{1}(V \leq p(Z)) \tag{4}$$

where $p(Z) = \Phi\left(Z'\gamma\right)$ and $V = \Phi\left(\eta\right)$ is the rank of η, which is uniformly distributed on $(0, 1)$ and independent of Z.

Under the assumption that (U, V) follows a bivariate Gaussian copula with dependence parameter ρ, independent of Z, Arellano and Bonhomme show that the model is defined as a location-shift Gaussian model and (3)-(4) simplifies to the Heckman Gaussian model:

$X'\beta\left(U\right) = X'\beta + \sigma\Phi^{-1}\left(U\right)$

However, the non-additive model (3)-(4) quantile curves are generally non-additive in the propensity score and covariates X. In absence of censoring, the linear quantile regression for

$$Q_\tau(Y^*, X) = X'\beta(\tau)$$

is characterized by:

$$\beta(\tau) = \arg\min_{b(\tau)}(\tau(Y^* - x'b(\tau))^+ + (1-\tau)(Y^* - x'b(\tau))^-),$$

where $a^+ = max(a; 0)$, $a^- = max(-a; 0)$.

That is the well known check function that characterizes the solution to the quantile regression problem. To address the issue of self-selection Arellano and Bonhomme (2016) propose to "rotate" that check function.

The quantile regression estimates corrected for selection proposed by Arellano and Bonhomme (2016) are given by,

$$\beta(\tau) = \arg\min_{b(\tau)} (G_{\tau Z}(Y^* - x'b(\tau))^+ + (1 - G_{\tau Z})(Y^* - x'b(\tau))^-)$$

and $G_{\tau Z} = G(\tau, \Phi(Z'\gamma); \rho)$ the conditional copula, denotes the rank of $x'b(\tau)$ in the selected sample $D = 1$.

The parametric version of the estimation procedure requires the following three steps (see Arellano and Bonhomme (2016) for a complete description):

- Step 1: Estimate γ using a probit regression
  $\widehat{\gamma} = \arg\max_{a} \sum_{i=1}^{N} D_i \ln \Phi(Z_i'a) + (1 - D_i) \ln \Phi(-Z_i'a)$
- Step 2: Estimate ρ (the copula parameter) by profiled GMM,
- Step 3: For any $\tau \in (0, 1)$, compute $\widehat{G}_{\tau i} = G(\tau, \Phi(Z_i'\widehat{\gamma}); \widehat{\rho})$ for all i, and estimate $\beta(\tau)$ by rotated quantile regression,

$$\widehat{\beta}(\tau) = \arg\min_{b(\tau)} \sum_{i=1}^{N} D_i[\widehat{G}_{\tau i}(Y_i - X_i'b(\tau))^+ + (1 - \widehat{G}_{\tau i})(Y_i - X_i'b(\tau))^-]$$

In this work we estimate a model where the actual level of debt is estimated, diverging from Cox and Japelli (1993) and Ruiz-Tagle and Vella (2015) who study the desired demand for credit. Thus, there is only one selection equation in our model, and the dependent variable of the first stage is a binary indicator that takes the value one if the household hold some debt. Moreover, the dependent variable of the equation for the intensive margin is the value of total household debts (in logs) for those that are indebted. As a consequence, the method is estimated exactly as described in Arellano and Bonhomme (2016) considering a two equation model with only one equation in the selection stage.

In our model, exclusion restrictions are given by four dummy variables. The first one captures liquidity needs (takes the value 1 if the respondent declares that the household's income was lower than expenditures in the previous year). In turn, the second one indicates that the household faced borrowing restrictions in the mortgage credit market while the third one indicates that the household faced borrowing restrictions in the consumer credit market. Finally, the fourth one indicates that the household has a business and faced borrowing restrictions in the corporate credit market.

4 Results

4.1 Extensive margin: Probit estimates

We estimate the extensive margin and the first stage of Arellano and Bonhomme estimator using a Probit model. In order to achieve identification we include two sets of covariates: variables that would affect the extensive and the intensive margin and variables that would affect only the extensive margin. We consider three alternative dependent variables: total debt, mortgage debt and consumer debt.

The first set of covariates includes: average years of schooling of members aged 18 or older, average age of members aged 18 or older (and its square), the value of real assets (log), an indicator that the household has at least one bank account, an indicator that the household has received inheritances, a categorical variable that captures working status: employee -the omitted category-, pensioner, informal business, formal business and inactive; income (log) and its square. Income (and its square) are interacted with each category of working status. The second set includes four variables that capture liquidity needs and borrowing restrictions, as we explained in the previous section.

Average Marginal Effects (AME) are reported in Table 6, and the AME evaluated at values along the support of the income covariate is illustrated in Figure 6. Income is not significant to explain the probability of being indebted. However, Figure 7 shows that for middle-income employees income has a small but positive effect. It is also remarkable that the point estimates of the average marginal effect of income over the probability of having any debt is somewhat hump shaped over the distribution of income for employees, pensioners and formal business owners, while for households with informal businesses it is increasing and for inactives is U-shaped.

The fact that income is not significant to explain the probability of being indebted does not conflict with the Permanent Income Hypothesis (PIH). This is because according with the PIH, it is the relationship of current income with permanent income that which influences households' credit demand.

Table 6 and Figure 6 also provide the AME of other relevant covariates. Years of schooling influences the probability of having mortgage debt positively, but negatively that of having consumer debts. The latter effect dominates and education negatively affects the likelihood that the household is indebted. The high cost of consumer credit in Uruguay could explain that result. The life cycle effect is captured by the model: the probability of being indebted increases with age for the youngest but decreases for those aged 40 or more. That pattern is stronger for consumer debt than for mortgage debt.

The magnitude of households' real assets does not affect the probability of being indebted, but it positively affects the stock of mortgage debt and negatively that of consumer debt. Those that have received inheritances has a lower probability of having mortgage debts but higher likelihood of having consumer debts.

Finally, all variables proposed as exclusion restrictions are highly significant and have the expected sign. Those households who declare that income was less than expenditures in the previous year are more likely to have debts. If the household had faced borrowing restrictions in the consumer segment of the credit market it has a lower probability of having consumer debt, but that covariate does not affect the probability of having mortgage credit. Facing restrictions in the market of mortgage credits positively impacts the probability of having debts, but that is the result of a negative effect in the mortgage segment and a positive effect in the consumer segment. Those households who run businesses and declared that their firms had faced restrictions in the corporate debt market also have a higher probability of having consumer debt.

4.2 Intensive margin: Conditional Quantile Regressions

In this section we present the results of the conditional quantile regressions for the intensive margin of debt holdings. Both uncorrected and selection-corrected models are computed, using respectively classical linear quantile regressions and Arellano and Bonhomme (2016) estimators to this end.[2] Table 7 reports coefficients and significance of each regressor. Point estimates and their standard errors are computed for each one of the 10 imputed datasets and afterwards Rubin's rules are applied.[3]. The dependent variables of the model are the magnitude of total debt and the stock of consumer credit.[4]

Income (log) enters into the model specification in a quadratic form and it is interacted with each category of employment status. We also include average years of schooling and a quadratic on age of households members aged 18 or older, value of real estate (log), a dummy that has bank account, a dummy that has received inheritances, employment status (employee -the omitted category-, pensioner, informal business, formal business and inactive). Exclusion restrictions (presented in the previous section) are included in the first stage of the Arellano and Bonhomme estimator.

The main parameter of interest of this work is the income elasticity of the debt stock over its conditional distribution. To this end we compute Conditional Quantile Partial Effects (CQPEs). But, to the extent that transformations of this variable are included, coefficients and standard errors should not be analyzed in an isolated manner. Figure 8 plots point estimates and 95th confidence intervals of income elasticity for employees, households with informal and households with formal business[5]. CQPEs are computed applying Slutsky's theorem and the Delta method at the median value of households' income[6].

Income elasticity of total debts is positive and significant at the 5 per cent level for the three groups at all quantiles, with the exception of the upper tail in the case of employees and the lower tail in the case of informal business. However, the magnitude of income elasticity differs remarkably among the three groups of households.

Those with formal business exhibit the highest level of sensitivity: income elasticity is

[2] We use the Matlab code provided by Arellano and Bonhomme.

[3] The variance-covariance matrix is computed from the bootstrapped empirical distribution of coefficients using 1,000 replications.

[4] The sample size of EFHU prevents us to study the intensive margin of mortgage debt.

[5] The red lines correspond to uncorrected estimates while the black ones are those of the selection-corrected estimates.

[6] The median value of income is calculated separately for each group of households depending on working status categories.

slightly decreasing along quantiles, but it is not significantly different than one at all quantiles. Elasticities of employees go from 0.65 at the bottom of the conditional distribution to zero at the higher tail, while that of households with informal businesses is almost constant around 0.5 along the conditional distribution. Selection-corrected CQPEs are smaller than uncorrected ones for employees, but in the case of households with formal or informal businesses corrected and uncorrected CQPEs are similar.

These results hold in general terms for consumer debts, but income elasticities are a bit lower, and in the case of informal business owners elasticities are not significant at the top tail (see Figure 9).

To investigate how does income elasticity change with the level of income we evaluate the CQPEs of income at percentiles 10 and 90 of the households' income distribution. Figures 10 and 11 show such estimates by household type.

The estimates are larger when we evaluate the selection-corrected CPQEs at the 90th percentile of households' income and the difference is large for the bottom half of the conditional debt distribution. The gap narrows along the conditional distribution of total debt.

More precisely, for employees, income elasticity is around 0.4 at quantiles 10 and 20 if it is computed using an income level that correspond to the 10th percentile of income among these type of households, while it is 0.9 if the computation is done using the 90th percentile of income. For households with formal (informal) businesses those figures are 0.7 and 1.2 (0.2 and 0.7), respectively. Concerning consumer debts there is also a positive relationship between point-estimated elasticities, but differences do not result statistically significant.

As for other covariates, we find that schooling has a positive effect, slightly increasing over quantiles in the case of total debts, and hump-shaped for consumer debts. Selection-corrected CQPEs are larger than uncorrected ones, but at the upper tail they are similar (Table 7).

The life cycle pattern is captured by a second order polynomial in the average age of adult household members, and evaluated at age 25, 45 and 65. The conditional quantile partial effect of age is positive at early stages of life and then turns negative (Figure 12). Such results hold at all percentiles of debt. The curve of CQPEs of age corrected for selection is flatter than the uncorrected one.

Finally, real assets and having bank accounts have a positive effect on the middle of the conditional distribution of total debts, but real asset is not significant for consumer debts; while have received inheritances negatively affects the magnitude of total household debts at all quantiles of the conditional distribution and does not affect consumer debts.

5 Conclusions

In this work we estimate a model for actual level of household debts. The focus is on the estimation of income elasticity, and the role of business ownership over that parameter. To this end, we estimate selection-corrected Conditional Quantile Regressions, using the Arellano and Bonhomme (2016) estimator.

The main result from the selection equation for the extensive margin is that income is not significant to explain the probability of being indebted. Schooling positively influences the probability of having mortgage debt, but affects negatively that of consumer debt. A life cycle pattern is captured by the model, and it is stronger for consumer debt than for mortgage debt.

The magnitude of households' real assets does not affect the probability of being indebted, but it positively affects the likelihood of having mortgage debt and negatively the probability of having consumer debt. Those households that have received inheritances have a lower probability of having mortgage debts but a higher likelihood of having consumer debts. Finally, all variables proposed as exclusion restrictions are highly significant and have the expected signs.

For the intensive margin, we estimate uncorrected and selection-corrected Conditional Quantile Regressions, using respectively classical linear quantile regressions and Arellano and Bonhomme (2016) estimators.

We find that income elasticity is positive and significant at the 5 per cent level for the three groups at all quantiles, with the exception of the top tail in the case of employees, and the bottom tail in the case of households with informal business. However, the magnitude of income elasticity differs remarkably among the three groups of households. Those with formal business exhibit the highest level of sensitivity. Selection-corrected CQPEs are smaller than uncorrected ones for employees, but in the case of households with formal or informal business corrected and uncorrected Conditional Quantile Partial Effects are similar.

Concerning other covariates, schooling has a positive effect, the effect of age is positive at early stages of life and then turns to be negative and real assets and having bank accounts have a positive effect on the middle of the conditional distribution of total debts. In addition, having received inheritances negatively affects the magnitude of household debts at all quantiles of the conditional distribution of total debts but does not affect the amount of consumer debts.

One clear policy-relevant implication of our results is that the stock of debt held by households will respond very differently to income shocks depending on the household's type and previous level of debt. For instance, we should expect to see almost one-to-one increases in debt stocks for households who own formal businesses and receive a positive income shock, even though they might already be highly indebted. Meanwhile heavily-indebted households whose income originates in salaried work would not increase their liabilities.

The previous example also highlights a gap in the literature, since, to our knowledge, a theoretical model that explains results such as ours is currently lacking. Such a model would need to take into account the role of business ownership and previous debt levels to determine the demand for credit in a context of underdeveloped financial markets.

Figure 1: Domestic credit to private sector (as % of GDP)

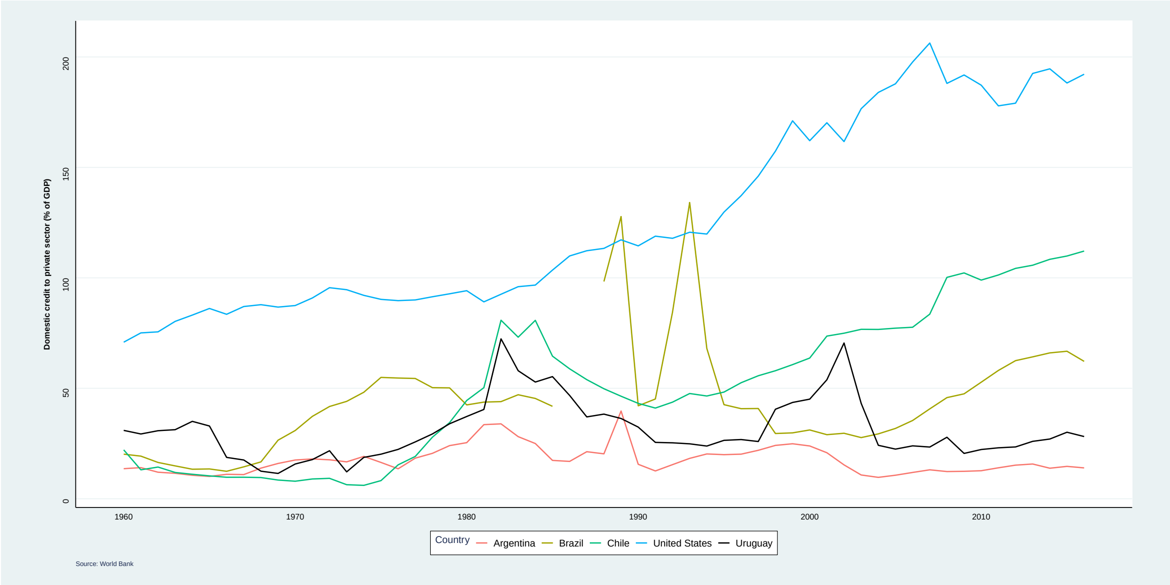


Figure 2: Interest rates (in %)

Figure 3: Percentiles of debt, by type of household

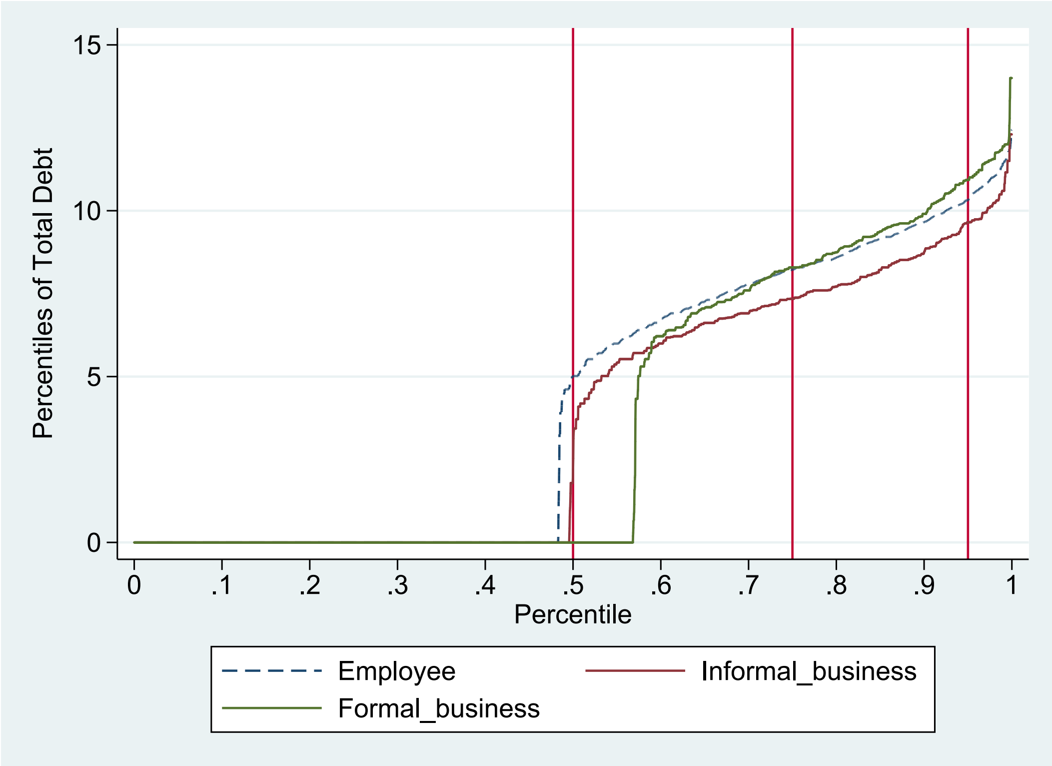


Figure 4: Debt and Income kernel density estimation. Indebted households
(x-axis scaled by an inverse hyperbolic sine transformation)

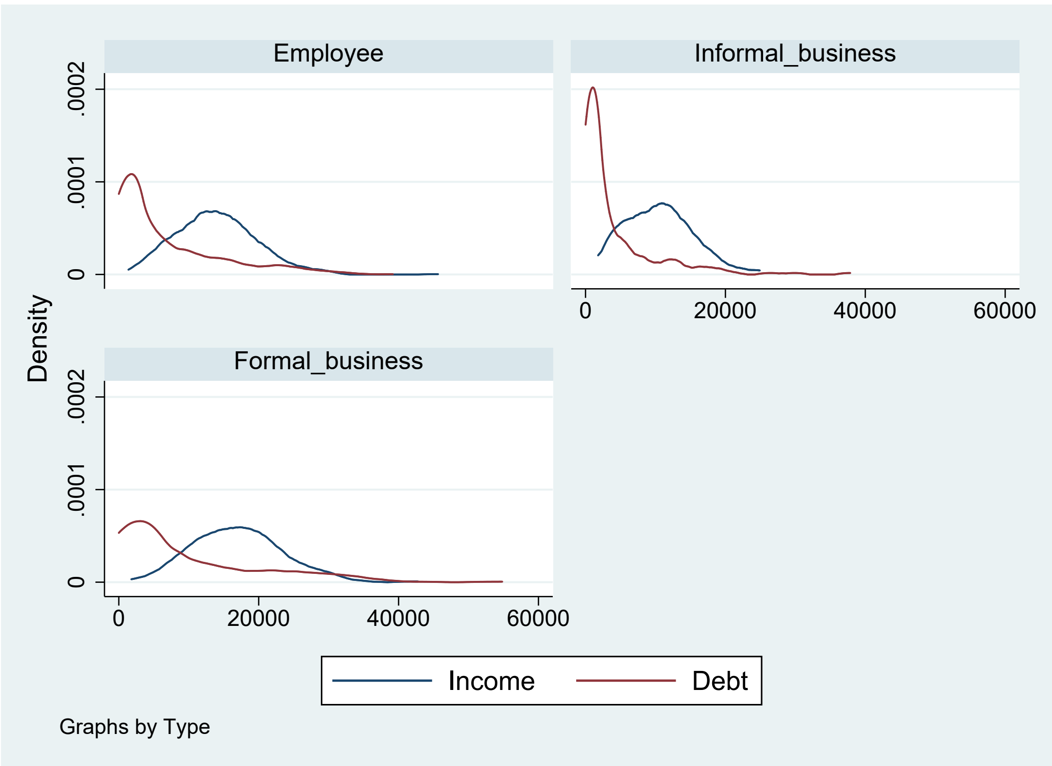
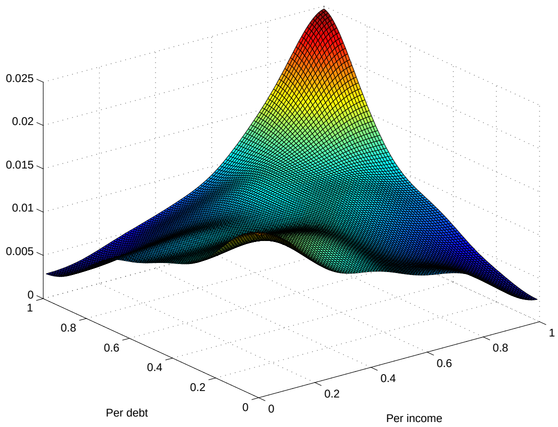
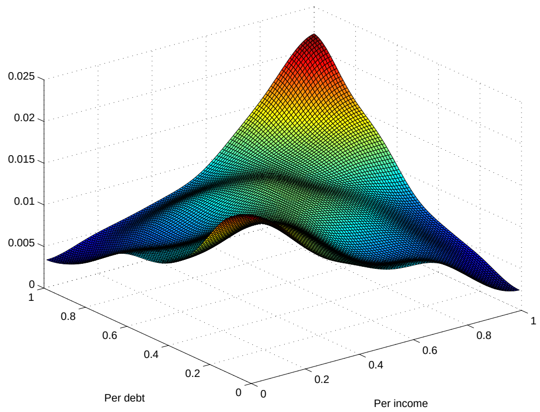


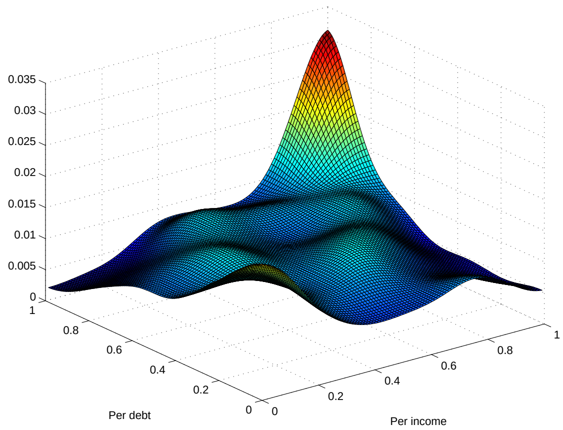
Figure 5: Non-parametric kernel smoothed copulas of income and debt. Indebted households



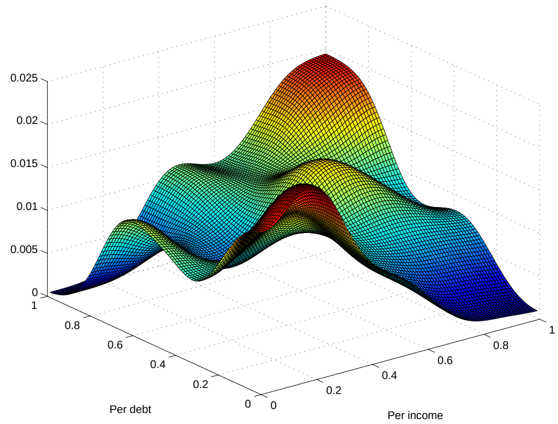
(a) Total



(b) Employees



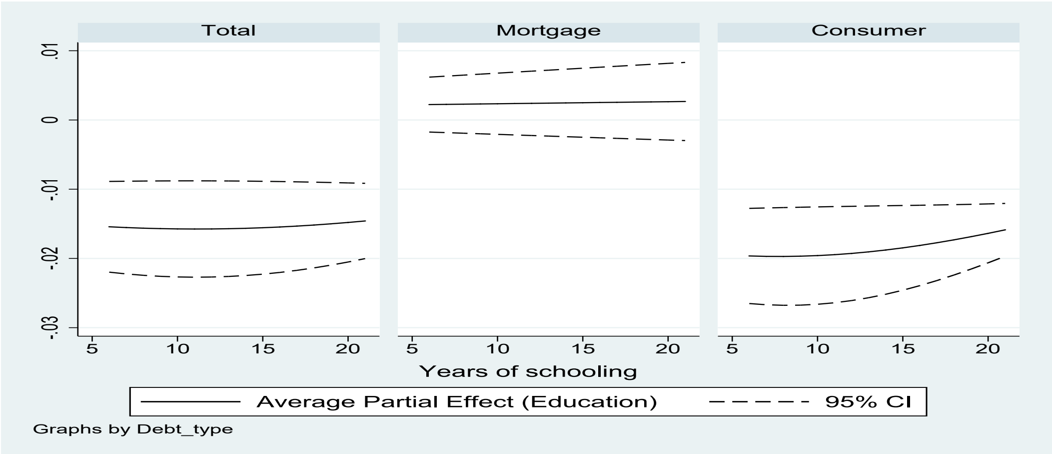
(c) Informal business



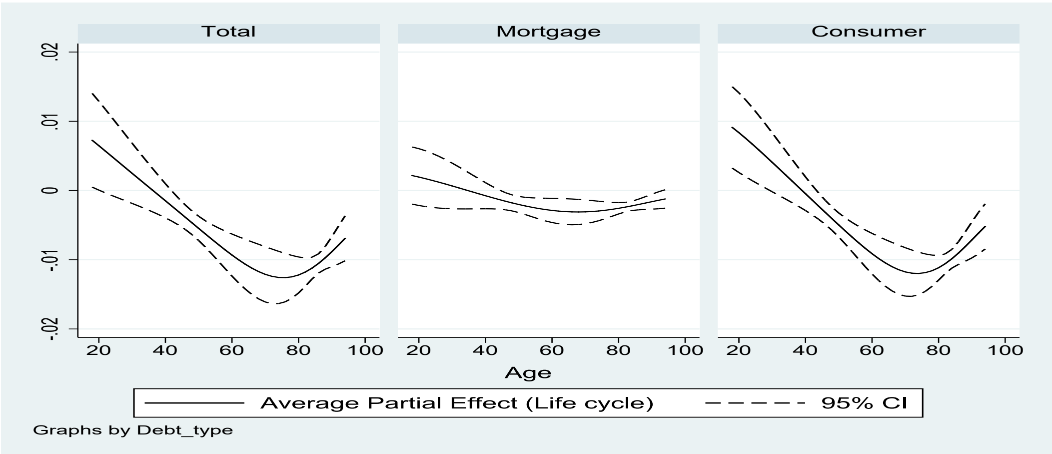
(d) Formal Business

Note: Non-parametric kernel copulas are built considering a bandwidth of 0.045. To deal with the "boundary bias" we use the "Mirror Image" technique (Deheuvels and Hominal, 1979; Schuster, 1985). We take all the different imputed sets for each survey. Sample weights were used in all cases.

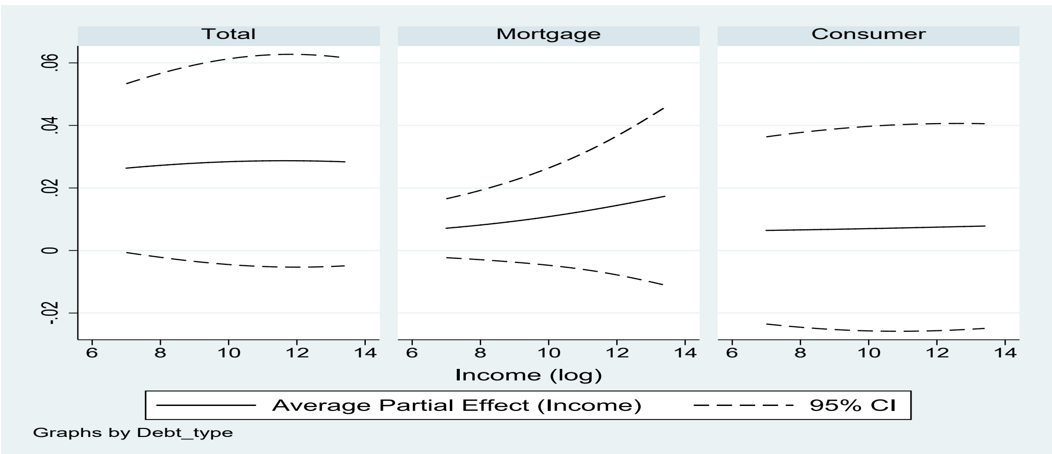
Figure 6: Average Marginal Effects on the probability of being indebted. 95% Confidence Intervals. Probit estimates



Years of schooling



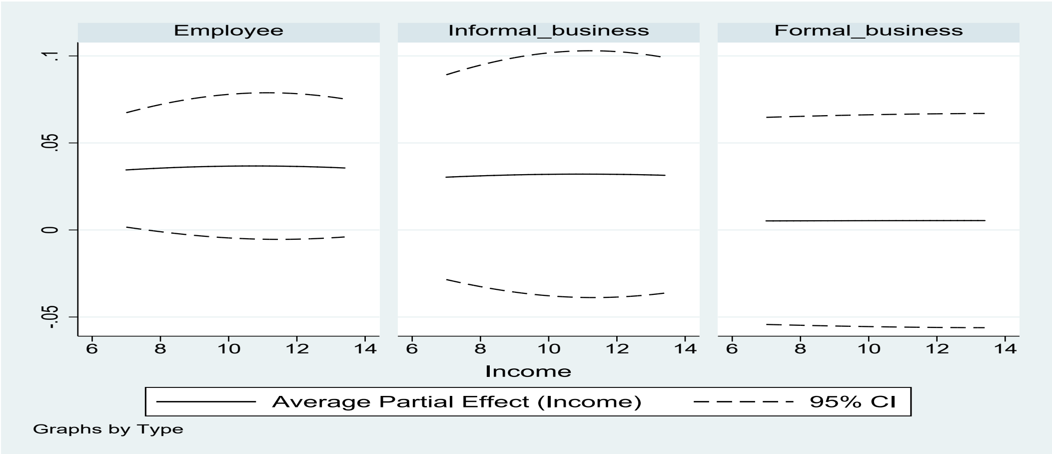
Life cycle



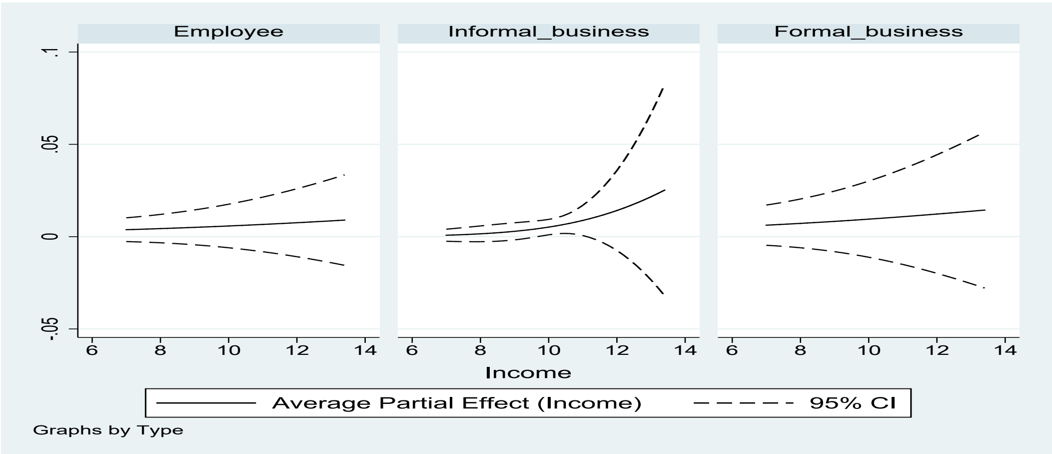
Income

.

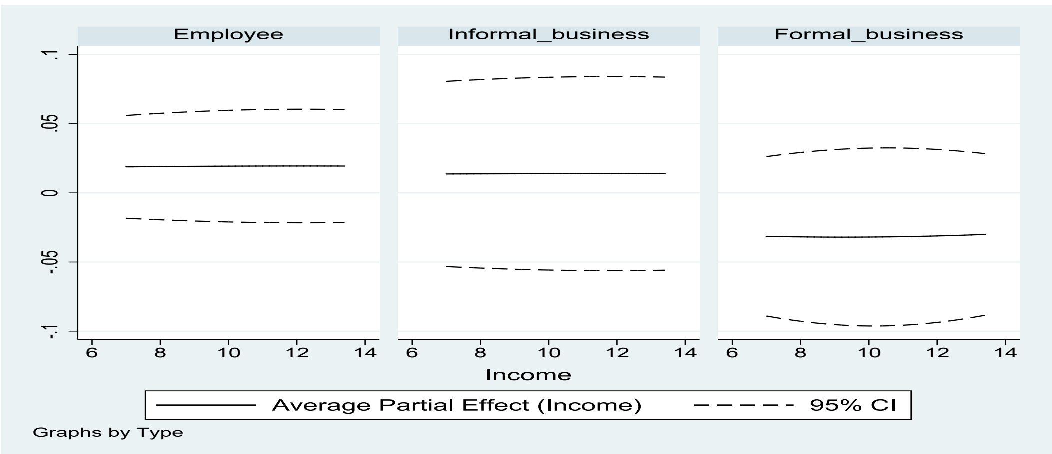
Figure 7: Marginal effect of Income (log) on the probability of being indebted. 95% Confidence Intervals. Probit estimates



Total debt

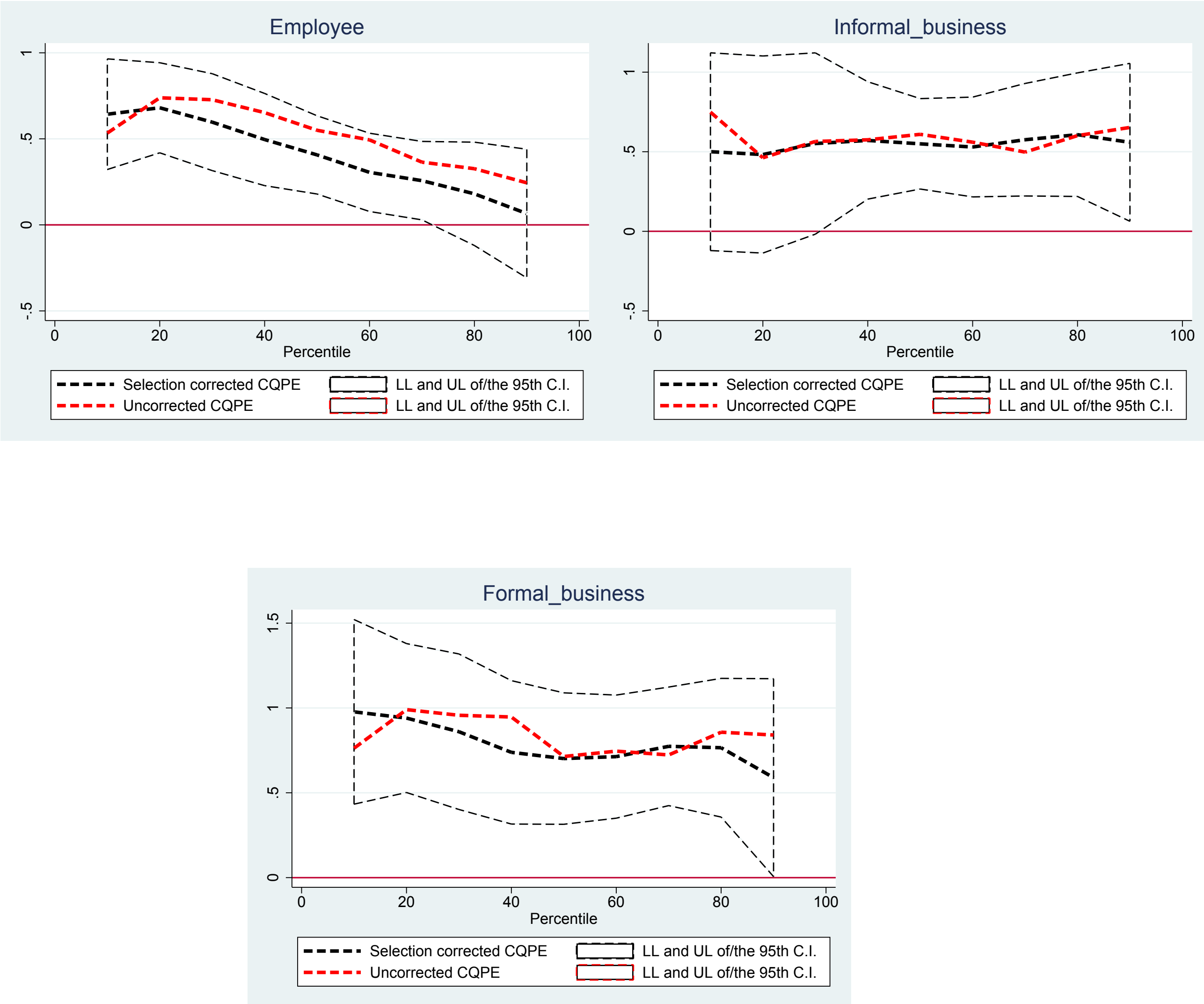


Mortgage debt



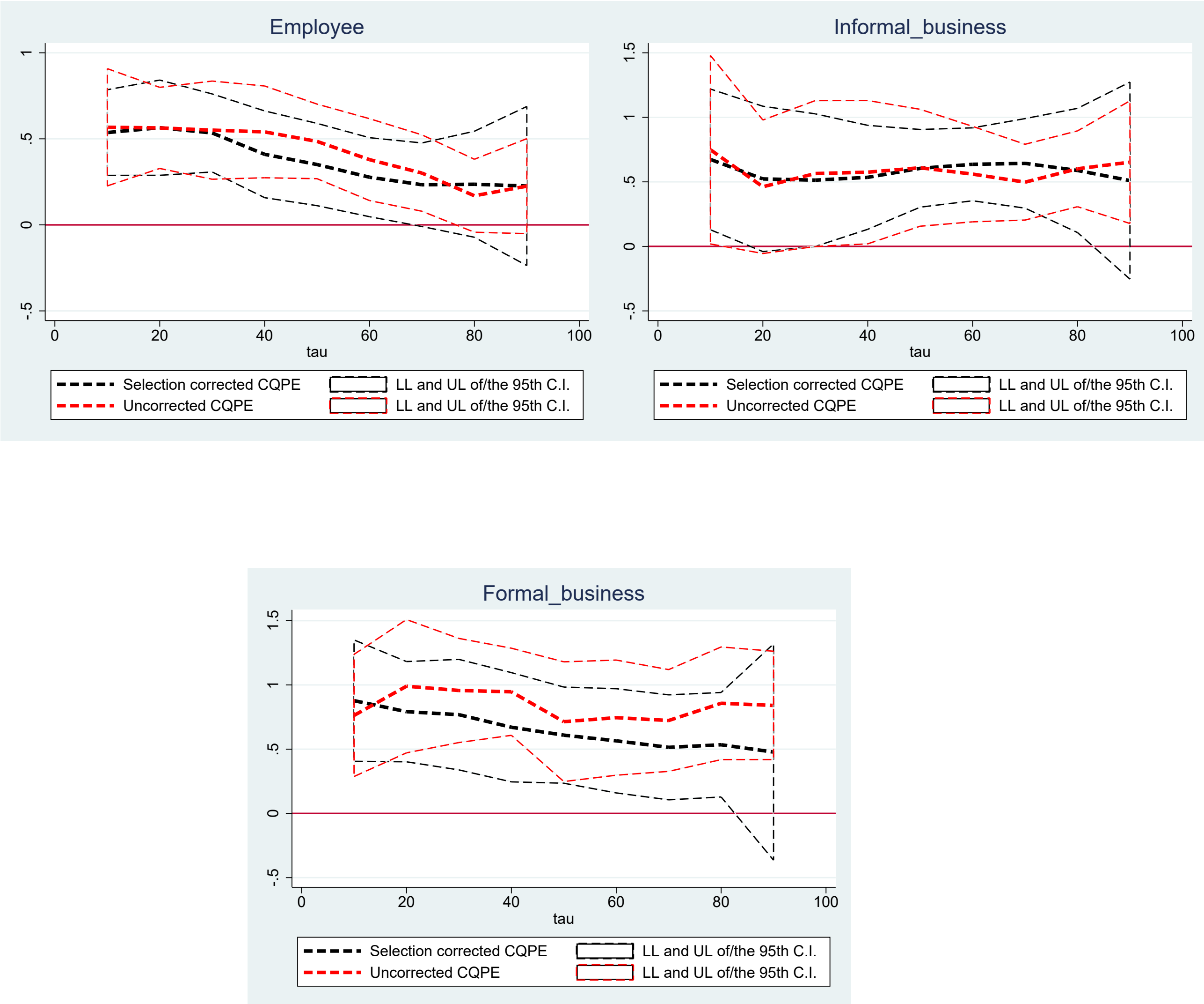
Consumer debt

Figure 8: Conditional Quantile Effect of Income on Household Debts



Figures are computed for the median value of income of each type of household

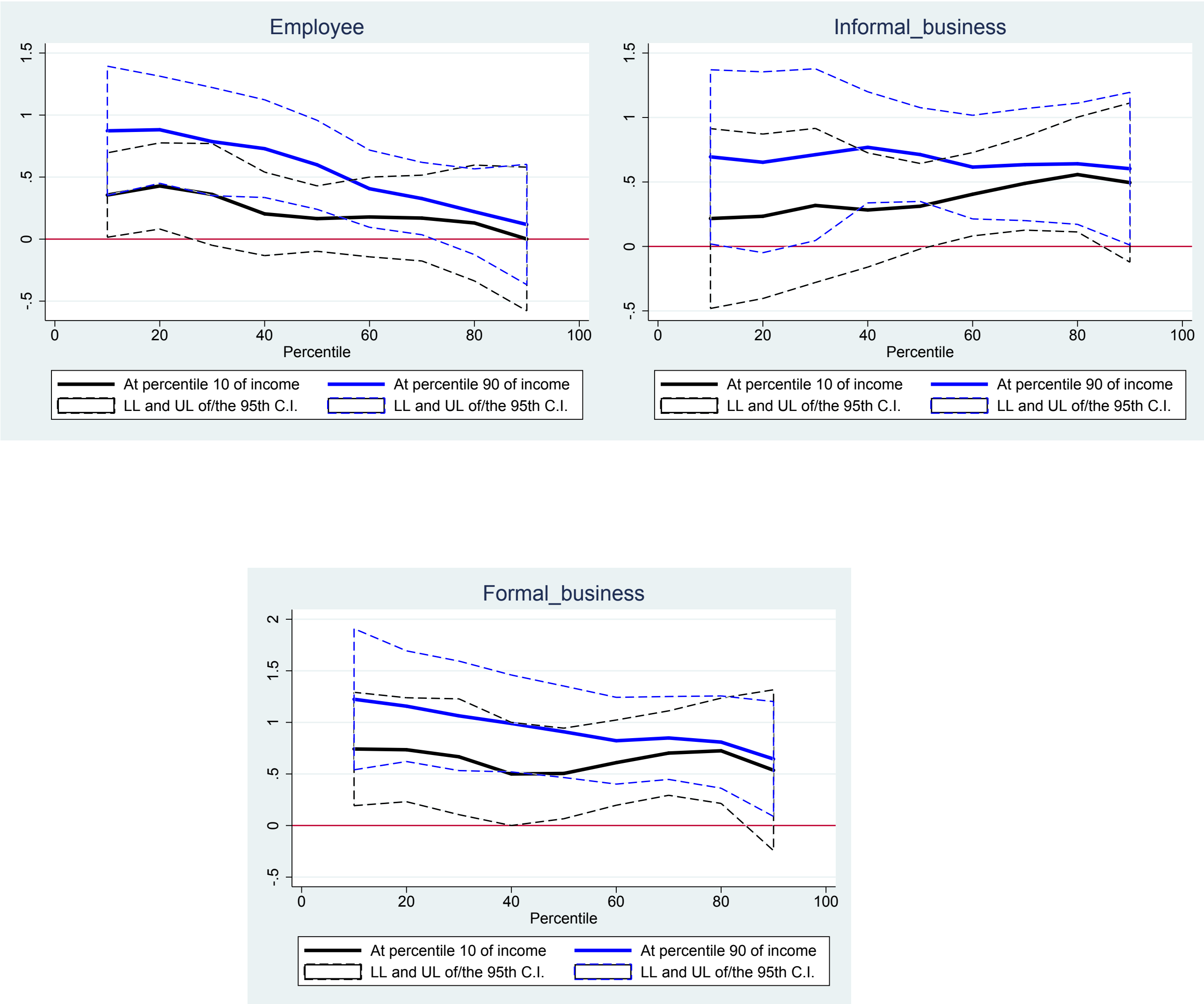
Figure 9: Conditional Quantile Effect of Income on Household Consumer Debts



Figures are computed for the median value of income of each type of household

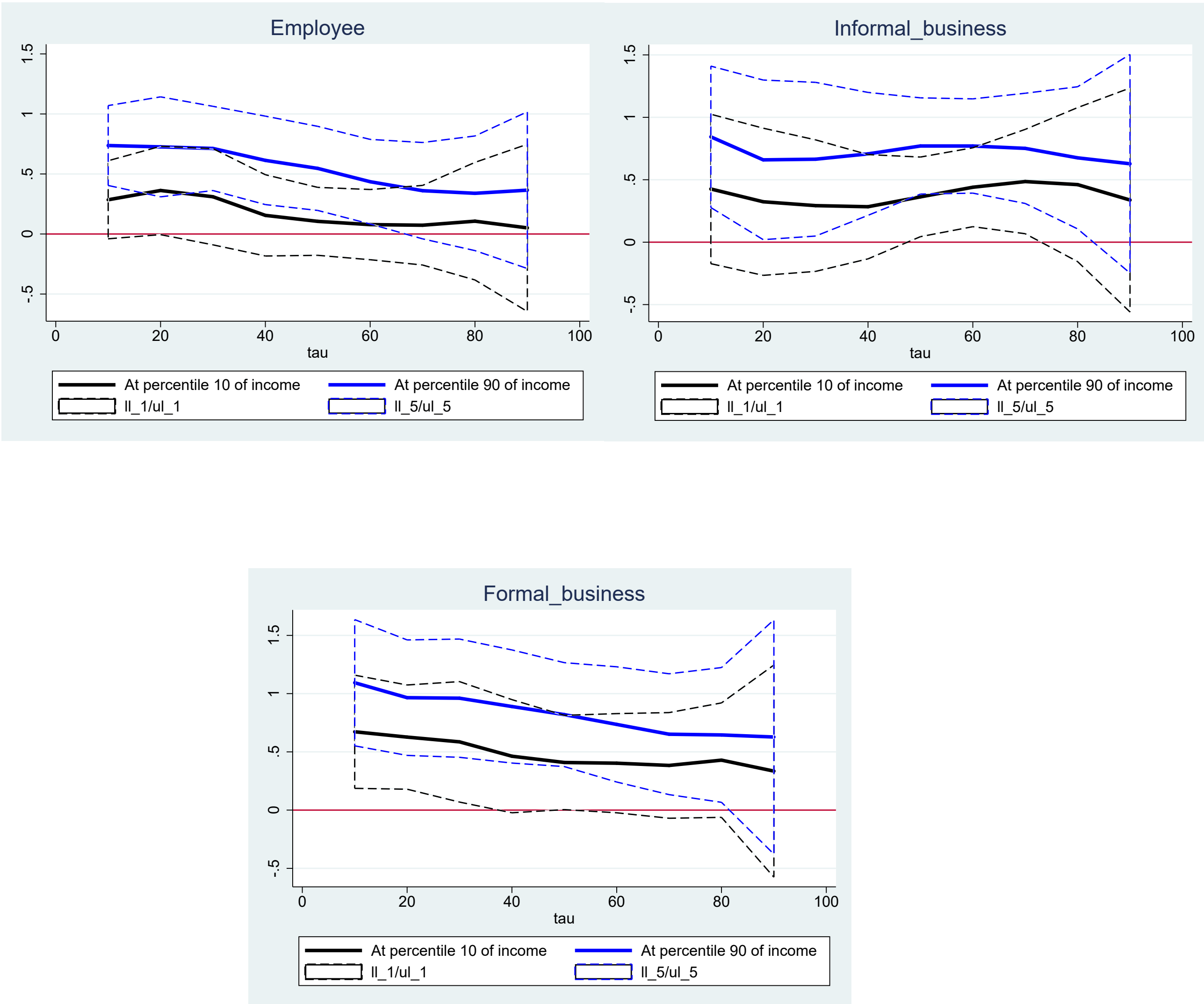
Figure 10: Selection-Corrected Conditional Quantile Effect of Income on Household Debts

(at alternative values for Income)



Figures are computed for percentiles 10 and 90 of income of each type of households

Figure 11: Selection-Corrected Conditional Quantile Effect of Income on Household Consumer Debts (at alternative values for Income)



Figures are computed for percentiles 10 and 90 of income of each type of households

Figure 12: Conditional Quantile Effect of Age on Household Total Debts

(at alternative values for Age)

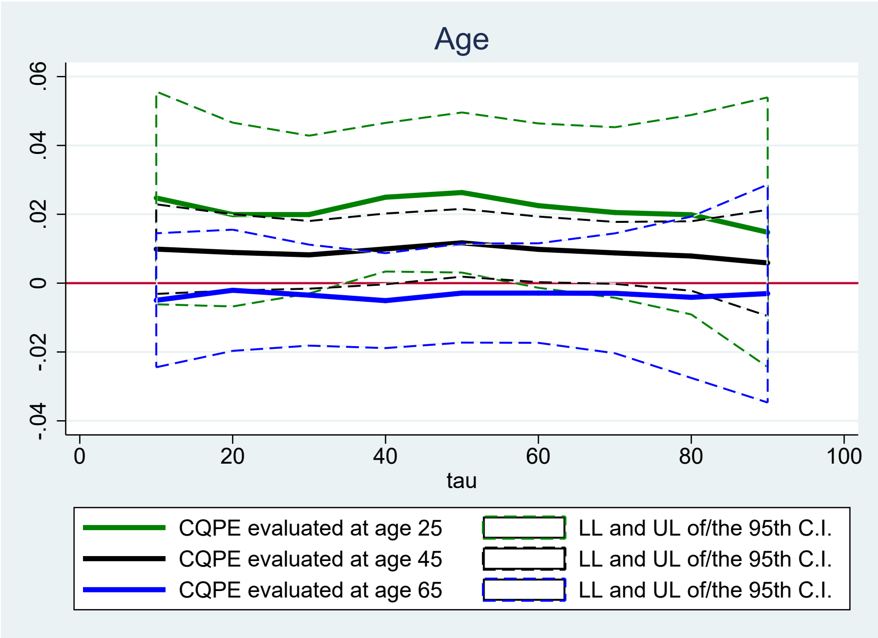


Figure 13: Conditional Quantile Effect of Age on Household Consumer Debts

(at alternative values for Age)

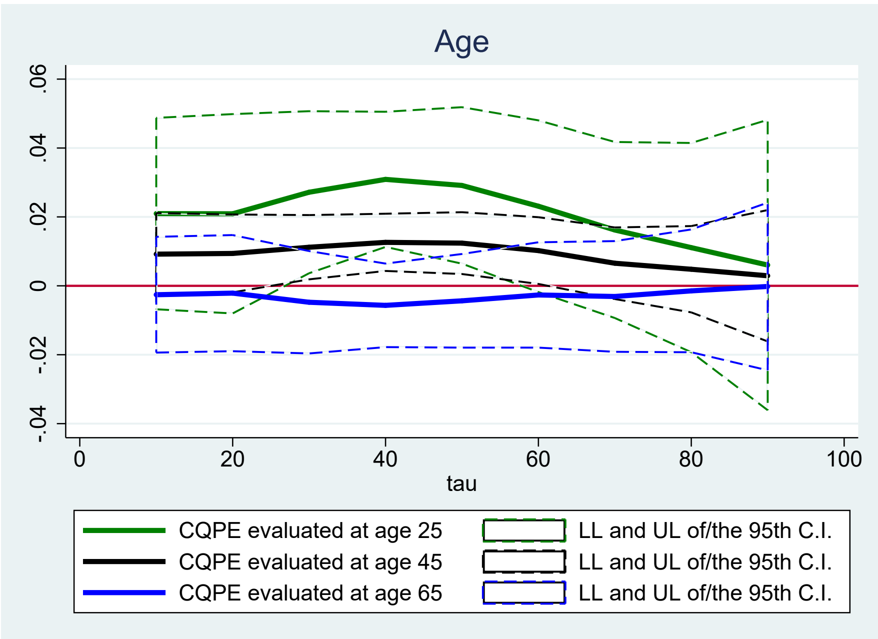


Table 1: Participation rates and allocation for household assets and debts

	Participation rate (% of households)	Median value (US dollar 2014)	Allocation (in %)
Financial assets	**48.9**	**6,900**	**4.5**
Non-financial assets	**85.2**	**85,448**	**95.5**
Main residence	61.7	60,000	55.2
Other real estate	12.7	70,920	23.4
Own business	20.9	262	12.2
Vehicles	56.9	5,000	4.5
Art, jewerly, other	3.6	2,173	0.2
Debts	**44.5**	2,467	
Main residence	8.0	13,608	52.3
Other real estate	1.2	15,962	9.2
Credit card	9.0	195	0.7
Consumption, vehicles	36.5	3,816	37.6

Notes: Participation rates are computed as the percentage of households owning each asset/liability. Median values are conditional on having each type of asset/liability. Statistics are computed using Rubin's rule over 10 imputation sets. Sample weights were used in all cases.

Table 2: Distribution of debts and credit constraints

	Prop. of HH	Income share	Total debt share	Mort. debt share	Cons. debt share	HH w/any debt	HH w/mort. debt	HH w/cons. debt	HH any constraint	HH Mort. constraint	HH Consum. constraint
Percentile of income											
I	20.0	5.2	6.9	2.4	13.6	46.8	2.9	45.3	48.3	31.2	36.6
II	20.0	9.9	10.8	7.5	15.7	44.2	7.0	41.5	41.6	27.6	28.2
III	20.0	15.1	14.1	10.8	18.8	53.2	7.2	49.8	39.2	26.3	23.4
IV	20.0	22.5	23.8	22.0	26.4	51.0	9.7	45.9	28.3	19.4	14.6
V	20.0	47.3	44.5	57.2	25.5	47.0	18.8	36.9	16.3	11.1	7.8
Age											
18-24	1.9	1.2	0.2	0.1	0.4	35.2	4.2	32.5	39.7	31.3	30.6
25-34	17.7	16.5	19.3	20.1	18.1	55.0	8.5	49.7	47.4	35.2	29.2
35-44	27.9	32.5	39.2	40.9	36.7	52.7	12.4	46.7	38.4	25.2	24.4
45-54	16.4	19.1	24.8	25.3	24.1	55.5	12.1	49.6	37.2	23.2	23.5
55-64	12.1	10.7	8.0	7.5	8.9	41.5	7.5	38.0	32.0	21.3	21.0
65+	24.0	20.0	8.4	6.1	11.8	38.5	4.9	36.2	20.5	12.1	13.2
Education											
Primary	20.3	10.6	5.7	2.6	10.2	41.3	2.7	39.9	37.2	23.2	26.1
Secondary	59.7	52.8	50.8	39.7	67.2	52.8	8.7	48.6	39.2	26.3	25.2
Tertiary	19.9	36.7	43.5	57.7	22.6	42.7	16.8	33.8	18.8	13.8	8.7
Region											
Rest of the Country	59.7	50.1	53.9	46.7	64.6	48.7	7.5	45.1	35.6	22.6	23.9
Montevideo	40.3	49.9	46.1	53.3	35.4	48.1	11.4	42.1	33.4	24.0	19.5
Employment status											
Inactive or unemployed	15.0	10.5	8.3	6.4	11.1	43.2	6.0	41.5	43.2	27.5	31.7
Pensioners	22.0	18.6	8.8	5.4	13.8	42.6	5.0	40.3	18.6	11.7	11.4
Employees	43.1	47.8	56.9	56.5	57.5	53.5	12.2	47.3	39.6	27.1	24.1
Informal business	10.3	7.2	7.4	7.3	7.6	53.0	5.9	49.2	46.4	32.9	30.3
Formal business	9.6	16.0	18.6	24.4	10.0	42.5	12.8	34.8	24.2	14.4	14.3

Source: EFHU.

Table 3: Participation rate for each type of debt, by type of household. Lower and upper limits of 95% confidence intervals, in percentages

	Employees		Informal business		Formal business	
	LL	UL	LL	UL	LL	UL
Any debt	51	56	48	58	37	48
Mortgage (Principal residence)	9	13	3	9	7	13
Mortgage (Other real estate)	1	2			2	5
Consumption debt	33	39	29	39	23	32
Credit card	11	15	6	13	5	9
Vehicles	6	9	3	8	4	9
Debt with goverment and public firms	9	13	12	20	4	10

Source: EFHU-2.

Table 4: Household liabilities conditional on having debts, by type of household (in 2014 US dollars)

	Employees		Informal business		Formal business	
	Mean	StD	Mean	StD	Mean	StD
Any debt	11,079	976	6,102	1,743	20,438	3,927
Mortgage (PR)	29,355	3,305	31,746	13,621	43,274	7,132
Mortgage (Other)	23,064	7,248			80,381	38,542
Consumption debt	5,425	692	2,432	270	5,287	681
Credit card	347	43	302	62	409	73
Vehicles	3,778	522	2,581	476	4,579	738
Debt with goverment and public firms	1,355	252	2,065	573	1,367	287

Source: EFHU-2.

Table 5: Percentiles of debt and debt to income and assets ratios, by type of household

Percentile	Employees	Informal business	Formal business
Debt (US Dollars)			
p10	294	150	550
p25	889	485	1387
p50	3240	1303	4504
p75	10773	4073	14337
p90	26667	10639	56800
Debt to annual income ratio			
p10	0.021	0.020	0.034
p25	0.063	0.048	0.073
p50	0.183	0.123	0.176
p75	0.592	0.364	0.633
p90	1.456	0.782	1.966
Debt to assets ratio			
p10	0.011	0.007	0.006
p25	0.048	0.022	0.017
p50	0.211	0.097	0.052
p75	0.746	0.493	0.191
p90	2.807	1.777	0.689

Source: EFHU-2.

Table 6: Probit estimates of the extensive margin. Average Partial Effects.

	Total debt		Mortgage debt		Consumer debt	
	(1)	(2)	(1)	(2)	(1)	(2)
Income (log)	0.010	0.009	0.014	0.012	-0.005	-0.009
Years of schooling	-0.013***	-0.013***	0.003*	0.003**	-0.015***	-0.014***
Age	-0.004***	-0.004***	-0.001**	-0.001**	-0.003***	-0.003***
Real assets (log)	0.002	0.002	0.021***	0.021***	-0.005***	-0.005***
Bank account	0.020	0.018	0.026**	0.025**	0.001	0.001
Inheritances	0.000	-0.002	-0.068***	-0.068***	0.049**	0.047**
Pensioner	0.007	0.005	-0.060***	-0.062***	0.043	0.040
Informal business	-0.030	-0.021	-0.029	-0.030	-0.023	-0.020
Formal business	-0.062**	-0.068**	-0.025*	-0.026*	-0.053*	-0.059**
Inactive	-0.079***	-0.069**	-0.038**	-0.038**	-0.048*	-0.041
Income less than expenditures	0.246***	0.248***	0.047***	0.048***	0.239***	0.241***
Borrowing constrained (consumption)	-0.296***	-0.293***	0.003	0.003	-0.327***	-0.322***
Borrowing constrained (mortgage)	0.071***	0.071***	-0.099***	-0.099***	0.091***	0.091***
Borrowing constrained (business)	0.116***	0.118***	0.024	0.024	0.104***	0.103***
Observations	3,483	3,483	3,483	3,483	3,483	3,483
Pseudo_R2	0.086	0.088	0.211	0.213	0.100	0.101
Wald_Test	0.000	0.000	0.000	0.000	0.000	0.000

Source: EFHU. *** p¡0.01, ** p¡0.05, * p¡0.1

All specifications include average years of schooling and a quadratic on age of households members aged 18 or older, value of real estate (log), a dummy that has bank account, a dummy that has received inheritances, employment status (employee -the omitted category-, pensioner, informal business, formal business and inactive). Two alternative specifications are used using income (log) in levels (columns 1) and a quadratic in that variable (columns 2). Income polynomial is interacted with each category of employment status. Finally, a dummy that capture liquid needs (take the value 1 if income was less than expenditures in the previous year) and three dummies that indicate that household faced borrowing restrictions in the consumer, mortgage and corporate credit market.

Table 7: Quantile regression estimates of the intensive margin. Total debts. With and without correction for selection.

	Heckman	Q10	Q20	Q30	Q40	Q50	Q60	Q70	Q80	Q90
Income (log)	-1.837*	-1.996	-1.684	-1.822	-2.357*	-1.921*	-0.993	-0.599	-0.308	-0.638
		-1.423	-1.753	-1.021	-1.099	-2.531*	-2.258*	-0.88	-0.529	0.06
Income (log) squared	0.115**	0.135	0.12	0.123	0.146**	0.119*	0.067	0.044	0.025	0.036
		0.099	0.127	0.089	0.089	0.157**	0.14**	0.063	0.043	0.009
Years of Schooling	0.099***	0.057***	0.07***	0.083***	0.093***	0.105***	0.116***	0.118***	0.111***	0.087***
		0.04	0.041**	0.052**	0.068***	0.075***	0.084***	0.104***	0.107***	0.088***
Age	0.237	0.039	0.03	0.034	0.041**	0.04*	0.034	0.031	0.03	0.024
		0.05	0.052**	0.048*	0.044*	0.051***	0.058***	0.047**	0.045*	0.042
Age squared	-0.0001	-0.001	-0.001	-0.001	-0.001*	-0.001	-0.001	-0.001	-0.001	-0.001
		-0.001	-0.001**	-0.001*	-0.001*	-0.001***	-0.001***	-0.001**	-0.001*	-0.001
Real assets (log)	0.0547***	0.025	0.037***	0.043***	0.05***	0.056***	0.064***	0.066***	0.071***	0.08***
		0.025	0.029**	0.03**	0.042***	0.047***	0.049***	0.064***	0.062***	0.072***
Bank account	0.210**	0.099	0.221	0.296**	0.372***	0.358***	0.326***	0.253**	0.172	0.077
		0.078	0.205	0.312**	0.305**	0.421***	0.405***	0.379***	0.256**	0.181
Inheritances	-.582***	-0.472**	-0.53***	-0.55***	-0.55***	-0.522***	-0.544***	-0.58***	-0.581***	-0.634***
		-0.359	-0.519***	-0.5***	-0.576***	-0.554***	-0.52***	-0.523***	-0.614***	-0.595***

Quantile regression estimates of the intensive margin. Total debts. With and without correction for selection. (cont.)

	Heckman	Q10	Q20	Q30	Q40	Q50	Q60	Q70	Q80	Q90
Pensioner	0.557	2.87	3.11	2.06	0.807	0.472	0.229	-0.623	-1.534	-2.607
		2.097	4.346**	4.383**	3.457*	1.741	1.32	1.674	0.138	0.275
Informal business	-1.985	-0.137	0.801	-0.452	-1.815	-2.271	-2.542	-3.382	-4.472*	-5.245
		-3.086	1.288	0.703	-0.044	-1.861	-1.893	-1.933	-3.126	-4.356
Formal business	-2.997*	-1.748	-1.594	-1.762	-1.658	-2.317	-3.56*	-4.689**	-5.465**	-4.793
		-1.241	-1.641	-1.572	-2.286	-0.572	-1.58	-3.054	-4.916***	-5.66**
Inactive	-1.577	2.567	2.655	2.265	1.02	0.218	-0.277	-0.776	-1.595	-4.103
		2.875	3	3.574*	3.181	1.648	1.13	0.516	-0.416	-0.561
Inc. x Pensioner	-.087	-0.301	-0.33	-0.215	-0.097	-0.082	-0.068	0.011	0.103	0.205
		-0.211	-0.458**	-0.46**	-0.357*	-0.187	-0.165	-0.216	-0.066	-0.088
Inc. x Inf.	0.178	-0.022	-0.112	0.034	0.177	0.217	0.242	0.329	0.432	0.498
		0.296	-0.174	-0.091	-0.006	0.186	0.179	0.184	0.31	0.415
Inc. x For.	0.328*	0.206	0.182	0.197	0.183	0.248	0.373*	0.49**	0.575**	0.506
		0.169	0.175	0.176	0.24	0.069	0.167	0.32	0.504***	0.59**
Inc. x Inac.	0.015	-0.264	-0.267	-0.223	-0.098	-0.024	0.02	0.059	0.126	0.374
		-0.314	-0.312	-0.371*	-0.327	-0.167	-0.128	-0.067	0.021	0.005
Constant	13.545***	11.22	10.222	11.498	14.661**	13.166**	9.521*	8.377	7.935	11.098
		8.555	9.84	6.732	7.731	15.264**	14.276**	8.588	7.644	6.034
N	1655	1655	1655	1655	1655	1655	1655	1655	1655	

Source: EFHU. *** p¡0.01, ** p¡0.05, * p¡0.1

Bootstrap standard errors are computed using 1,000 replications in each set of imputed data. Afterwards, Rubin's rules are applied.

Table 8: Quantile regression estimates of the intensive margin. Consumer debt. With and without correction for selection.

	Heckman	Q10	Q20	Q30	Q40	Q50	Q60	Q70	Q80	Q90
Income (log)	-2.376**	-1.776	-1.295	-1.525	-1.935	-1.907*	-1.552	-1.239	-0.953	-1.383
		-1.758	-0.976	-0.301	-0.24	-1.368	-1.224	-1.189	-0.321	-0.41
Income (log) squared	0.142***	0.117**	0.094	0.105	0.119*	0.115**	0.093	0.075	0.06	0.082
		0.118	0.078	0.043	0.039	0.094	0.081	0.076	0.025	0.032*
Years of Schooling	0.061***	0.028	0.034*	0.037*	0.048**	0.06***	0.064***	0.062***	0.054***	0.041
		-0.009	0.01	0.016	0.015	0.012	0.033*	0.047***	0.05***	0.034
Age	0.018	0.035	0.035	0.047**	0.053***	0.05**	0.039*	0.028	0.018	0.009
		0.042	0.048**	0.054**	0.061**	0.072***	0.071***	0.064***	0.054**	0.037
Age squared	-0.001	-0.001	-0.001	-0.001*	-0.001***	-0.001**	-0.001	-0.001	-0.001	-0.001
		-0.001	-0.001**	-0.001**	-0.001**	-0.001***	-0.001***	-0.001***	-0.001**	-0.001
Real assets (log)	0.011	-0.007	-0.001	0.001	0.004	0.007	0.007	0.008	0.011	0.008
		-0.019	-0.019	-0.016	-0.011	-0.014	-0.008	0	-0.003	-0.002**
Bank account	0.213**	0.01	0.256*	0.352***	0.409***	0.384***	0.361***	0.338***	0.253*	0.099
		0.041	0.06	0.313**	0.384***	0.48***	0.464***	0.399***	0.361***	0.265
Inheritance	-0.243**	-0.165	-0.241	-0.188	-0.165	-0.131	-0.08	-0.109	-0.151	-0.049
		-0.024	-0.155	-0.139	-0.157	-0.069	-0.121	-0.099	-0.043	-0.084

Quantile regression estimates of the intensive margin. Consumer debts. With and without correction for selection. (cont.)

	Heckman	Q10	Q20	Q30	Q40	Q50	Q60	Q70	Q80	Q90
Pensioner	-0.54	1.087	1.144	0.566	-0.42	-0.62	-0.93	-1.219	-1.621	-2.135
		2.49	2.312	2.642	2.171	1.567	0.631	-0.318	-0.371	-0.865
Informal business	-2.634	-2.353	-0.413	-0.665	-2.16	-3.419*	-4.261**	-4.619**	-4.022	-3.597
		-4.246	-1.786	0.99	-0.642	-0.676	-1.384	-3.818**	-4.096**	-3.984
Formal business	-2.489	-2.232	-1.374	-1.502	-1.688	-1.821	-2.264	-2.236	-2.499	-1.897
		-0.072	-1.303	-1.341	-0.932	-1.798	-1.395	-1.682	-2.572	-1.576
Inactive	-0.981	2.154	1.649	1.09	-0.067	-0.639	-1.512	-1.921	-2.113	-3.731
		2.651	2.84	2.52	1.955	0.832	-0.086	-0.534	-1.813	-1.086
Income x Pensioner	0.048	-0.092	-0.101	-0.039	0.056	0.059	0.082	0.112	0.143	0.168
		-0.213	-0.209	-0.249	-0.201	-0.139	-0.052	0.029	0.028	0.078
Income x Informal	0.258	0.233	0.035	0.064	0.221	0.347*	0.434**	0.47**	0.401	0.35
		0.445	0.177	-0.11	0.059	0.067	0.137	0.396**	0.418**	0.403
Income x Formal	0.279	0.27	0.17	0.171	0.188	0.189	0.232	0.235	0.261	0.202
		0.067	0.165	0.168	0.103	0.195	0.151	0.166	0.259	0.169
Income x Inactive	0.115	-0.213	-0.149	-0.086	0.028	0.079	0.167	0.202	0.206	0.356
		-0.259	-0.289	-0.251	-0.195	-0.071	0.016	0.057	0.19	0.096
Constant	16.834***	11.076**	9.117	10.521	13.184**	13.69***	12.901**	12.281*	11.645	14.806
		10.701	7.227	4.129	4.118	9.871	9.807	10.442**	7.511	8.836
N		1,487	1,487	1,487	1,487	1,487	1,487	1,487	1,487	1,487

Source: EFHU. *** p¡0.01, ** p¡0.05, * p¡0.1

Bootstrap standard errors are computed using 1,000 replications in each set of imputed data. Afterwards, Rubin's rules are applied.

References

Arellano, M. and S. Bonhomme (2016). Sample selection in quantile regression: A survey. Chapter, *Handbook of Quantile Regression*, edited by Roger Koenker, Victor Chernozhukov, Xuming He, and Limin Peng.

Cox, D. and T. Japelli (1993). The effect of borrowing constraints on consumer liabilities. Boston College Working Papers in Economics 228, Boston College Department of Economics.

Deheuvels, P. and P. Hominal (1979, 01). Estimation non parametrique de la densité compte tenu d'informations sur le support. *Revue de Statistique Apliquée 27*, 47–68.

Fairlie, R. and H. Krashinsky (2012). Liquidity constraints, household wealth, and entrepreneurship revisited. *Review of Income and Wealth 58*(2), 279–306.

Heaton, J. and D. Lucas (2000). Portfolio choice and asset prices: The importance of entrepreneurial risk. *The journal of finance 55*(3), 1163–1198.

Heckman, J. J. (1979). Sample selection bias as a specification error. *Econometrica 47*(1), 153–161.

Hurst, E. and A. Lusardi (2004). Liquidity constraints, household wealth, and entrepreneurship. *Journal of Political Economy 112*(2), 319–347.

Martin, P. and T. Philippon (2017, July). Inspecting the mechanism: Leverage and the great recession in the eurozone. *American Economic Review 107*(7), 1904–37.

Mian, A. and A. Sufi (2010). Household leverage and the recession of 2007–09. *IMF Economic Review 58*(1), 74–117.

Mian, A. and A. Sufi (2018, August). Finance and business cycles: The credit-driven household demand channel. *Journal of Economic Perspectives 32*(3), 31–58.

Ruiz-Tagle, J. and F. Vella (2015). Borrowing constraints and credit demand in a developing economy. *Journal of Applied Econometrics 31*(5), 865–891.

Zinman, J. (2015). Household debt: Facts, puzzles, theories, and policies. *Annual Review of Economics 7*(1), 251–276.