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THE DETERMINANTS OF HOUSEHOLD DEBT DEFAULT

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Abstract
Based on a new dataset obtained from survey data, we study household debt default behavior in Chile. Previous research in this area suggests financial and personal variables that can help estimate individual and group probabilities of default. We study mortgage and consumer default separately, as the default decisions and overall borrower behavior are different for each type of debt. Our study finds that income and income-related variables are the only significant and robust variables that explain default for both types of debt. Demographic or personal variables are specific to one or the other type of debt but not to both. For example, level of education is a factor that affects mortgage default, whereas the determinants of consumer debt default include the age of the household head, and the number of people within the household that contribute to the total family income. We derive threshold probabilities of default for each type of debt and compare them to those obtained from results of previous work based on the same Chilean data, but with a different approach. We find that the probability of default decreases as the family income increases, and that our estimates are consistent with other studies similar to ours. Also consistently with previous research, we find that, in terms of the distribution of debt and default risk, the largest portion of the country's household debt is in the hands of families in the upper quintiles, who have the lowest risk of default. This implies that the overall financial system should be relatively stable, even in the face of moderate macroeconomic shocks.

Resumen
En base a datos obtenidos de una encuesta, estudiamos el comportamiento de no-pago de deudas de los hogares en Chile. Investigaciones anteriores sobre este tema sugieren variables de tipo financiero y personal que pueden ayudar a estimar la probabilidad de no-pago para individuos y grupos de personas. Estudiamos el no-pago de deuda hipotecaria y de consumo por separado, ya que tanto la decisión de no-pago como el comportamiento del deudor son distintos en los dos casos. Nuestro estudio encuentra que el ingreso y las variables relacionadas con este son las únicas robustas y significativas que explican el no-pago de ambos tipos de deuda, mientras que las variables demográficas o personales tienden a estar relacionadas con uno u otro tipo de deuda, pero no con ambos. Por ejemplo, el nivel de educación es un factor que afecta el no-pago hipotecario, mientras que en los determinantes del no-pago de la deuda de consumo resultan significativos la edad del jefe del hogar y el número de personas en el mismo hogar que contribuyen al ingreso total de la familia. A su vez, derivamos probabilidades límite de no-pago para cada tipo de deuda y las comparamos con aquellas obtenidas en estudios previos basados en los mismos datos pero utilizando una metodología distinta. Encontramos que la probabilidad de no-pago disminuye a medida que el ingreso del hogar aumenta, y que nuestras mediciones son coherentes con las obtenidas por otros autores. En coherencia con resultados de investigaciones previas, encontramos que, en términos de la distribución de la deuda y el riesgo de no-pago, la mayor parte de la deuda vigente en el sistema crediticio nacional está en manos de hogares en los quintiles superiores de ingreso, los que tienen las menores probabilidades de no-pago. Esto implica que el sistema financiero debería ser relativamente estable, incluso ante eventos macroeconómicos adversos de tamaño moderado.

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1. Introduction

In the present paper we study the determinants of debt default at the household level in Chile. Using a dataset obtained from the Survey of Household Finances (*Encuesta Financiera de Hogares*, EFH, 2007), we estimate various specifications of a probit model in search of the characteristics, both personal and financial, that have the highest impact on the overall probability that a household will default on its outstanding debt. We test a range of explanatory variables that have been identified by previous theoretical and empirical studies as being influential in a person's decision to stop debt repayments. Since the very structure of the types of debt differs and thus so do the determinants of default, we choose to analyze securitized (mortgage) and non-securitized (consumer) debt separately. We find that, for both types of debt, income is a significant and robust predictor of default risk, be it as a direct continuous variable, an indicator for income-quintile groups, or as other variables that are highly correlated with income and therefore act as proxies for it, like owning a bank account. For mortgage debt the level of education of the head of the family is a significant determinant, while for consumer debt the age and age squared of the household head are also factors. Debt service ratio is also tested as an independent variable and is found to be of importance in determining consumer debt risk only, as are various controls for the number of people who contribute to the family income.

We then estimate threshold probabilities of default (TPDs) that characterize the sample, which permit this study to be compared to the previous work of Fuenzalida and Ruiz-Tagle, 2009 (F-RT) which is based on the same data, as well as constituting a form of robustness test for the models employed. We find that TPDs are intuitive in that the probability of default decreases as income increases and also that they are close to the numbers obtained by using data and parameters used by F-RT, but higher, indicating that the ones based on F-RT's conditions are more strenuous than ours. This is consistent with the fact that F-RT perform a stress test of household finances via a macroeconomic shock that increases job loss probabilities, while ours are based on a non-stressed situation.

The main contributions of this paper are to test and validate various variables with readily available information as potential determinants of household debt default in Chile and, through econometric analysis performed on the household debt dataset, establish that the larger portions of outstanding debt in Chile are in the hands of borrowers that are less vulnerable to macroeconomic or systemic shocks, indicating that the Chilean financial system is relatively robust to these risks.

The rest of this paper is organized as follows. In section 2 we review some of the extensive literature on various aspects of personal and household finances and default. Section 3 describes the data and presents sample statistics. Section 4 contains the econometric analyses and their results. In section 5 we estimate and study threshold values for the probability of default (PD) and, finally, section 6 contains concluding remarks and directions for further study.

2. Literature Review

Studies that look into debt default at the household level are mostly empirical in nature and oriented towards credit scoring as can be seen, for example, in the survey by De Vaney and Litton (1995). Although related to this paper, credit scoring is more concerned with developing a multitude of ratios, algorithms and models so that lenders can discriminate between good payers and potentially bad ones, than with explaining the possible causes or determinants of default.

There is abundant literature analyzing non-performing mortgages on one hand and credit card and other non-securitized or “consumer” forms of debt default on the other[1]. We speculate debtor behavior to be different for these two types of debt, and, in keeping with the literature, we proceed to study mortgage and consumer debt default separately.

In terms of a theory model, Jackson and Kasserman (1980) discuss two alternative scenarios that could describe home mortgage default behavior. The “equity theory of default” involves rational borrowers who attempt to maximize the equity position in the mortgaged property at each point in time. They cease payments if the market value of the mortgaged property declines sufficiently in relation to the outstanding mortgage loan balance at any time. The alternative explanation is based on cash flows, and termed the “ability to pay” theory of default. Under this theory, debtors will avoid defaulting on their debts as long as their income flows are sufficient to cover the

[1] This classification comes naturally from the difference between securitized and non-securitized debt. Mortgages are considered securitized (explicitly backed by real estate as collateral), while other forms of debt, which range from bank loans and car loans to department store credit cards and even friends and family loans, are not.

mortgage payments without undue stress. Wong et al. (2004) attempt to identify the main determinants of mortgage default behavior in terms of these two theories, and state that under the profit maximization theory the current loan-to-value ratio, LTV (the ratio between the amount lent and the current value of the property), should be the most important factor in the borrower's decision to default. On the other hand, under the ability to pay paradigm, the current debt service ratio, DSR (the proportion of income that is used to pay off debt), should play a major role in the decision to default. Although this insight contributes an identifying condition to discern between the two proposed models, Wong et al. are unable to find support for either theory as these variables are insignificant in their study.

These variables have been studied in previous research. Campbell and Dietrich (1984), Vandell and Thibodeau (1985), Lawrence et al. (1992), Mills and Lubuele (1994) and Deng et al. (1995) all conclude that the LTV ratio is a strong determinant of mortgage loan default risk and also show that their relationship is positively correlated. On the other hand, Stansell and Millar (1976), Vandell (1978) and Ingram and Frazier (1982) confirm the importance of DSR as an explanatory variable of this type of default.

Aside from financial variables, various authors conclude that personal characteristics such as education, income and gender are as important in explaining default (if not more so) as those described above (see for example, Morton (1975), Ingram and Frazier (1982), Webb (1982), Aylward (1984), Waller (1988), Canner et al. (1991) and Lawrence and Arshadi (1995)). Indeed, simulation results from Vandell and Thibodeau (1985) show that several nonequity factors dominate the equity effect on default, which helps to explain why some households with zero or negative equity may not default, while others with positive equity may do so.

Avery et al. (2004) find that longtime married individuals have lower rates of default than recently married or divorced individuals. This is because married couples are less sensitive to income shocks, perhaps because they tend to have two incomes. Regarding gender, male subjects tend to have higher probabilities of default. Sharma and Zeller (1997) argue that females are less likely to default because they choose less risky projects. This is also confirmed by Stavins (2000), who tests the determinants of credit card delinquency and default, and finds that married couples, older individuals, better educated and higher income individuals all have a lower probability of default.

Given that the present financial crisis was sparked by a massive default on personal debt, it becomes clear that a region's financial stability can be potentially affected by personal accounts at the aggregate level. However, there has been little development in the study of personal finances[2]. In a paper that closely resembles the methodology and data found here, Pham and Lensink (2008) study the determinants of access to different types of credit (formal, informal and semi-formal) and the PD of debtors in Vietnam. The main aim of their investigation is to establish differences in these determinants for the different types of lenders. Pham et al. (2008) conclude that the determinants of default vary according to the type of lender. While informal lenders face a higher rate of default, it is possible for them to mitigate this effect by lending to family members or other individuals with close relationships. On the other hand, for formal lenders the most relevant determinants of default involve the characteristics of the debt contract, such as interest rate and loan duration. Other results show that men tend to have higher PDs, while being married tends to reduce a person's PD, as in Avery et al. (2004).

Finally, using the same dataset that we use, EFH-2007, Fuenzalida and Ruiz-Tagle (2008) study the impact of potential job loss (as a proxy for the main source of income) in the levels of debt default, aggregating the results to study the effects on the stability of the Chilean financial system. Their main conclusion is that, more often than not, outstanding personal debt in Chile is in the hands of people for whom the probability of job loss is relatively low, and hence the overall risk faced by the financial system is moderate.

3. Data description

In order to study personal default behavior in Chile, we use data from the EFH-2007 which is similar in design to surveys regularly carried out in the U.S. (the Federal Reserve's Survey of Consumer Finances, SCF), and various European countries, for example, the EFF (*Encuesta*

2 John Campbell (2006) points this out in his presidential address at the American Finance Association (AFA) conference, and goes on to show that, although most homes make relatively good investment decisions, those with lower income and education tend to make suboptimal investment choices, resulting in what he describes as a cross-subsidy from naïve to sophisticated households, which can inhibit welfare-improving financial innovation.

Financiera de las Familias) in Spain, and the SHIW (Survey of Households' Income and Wealth) in Italy.

Taken in Chile for the first time in 2007, the survey contemplates various areas that include personal and household data, information regarding employment, income, assets, debt, insurance, savings and investments, amongst others. The sampling design is skewed towards households with higher incomes mainly for two reasons: first, to provide a more precise estimate of wealth in general and of narrowly held assets and, second, to better compensate for nonresponse, which is differentially higher amongst the wealthy as can see in Kennickell (2008) and Barceló (2006) Therefore, expansion factors are used in all statistics and estimates to make results representative at the national/urban level. Financial information from the survey is aggregated at the household level. However, when we use individual data as part of our analyses, this information corresponds to the head of the surveyed household, who is defined as the main provider of household income.

Table 1
Income per quintile without imputed bases (1)

Quintile	Number of Homes	Minimum	Maximum	Mean	Median
Q1	977,410	24	633	405	420
Q2	941,365	634	1,160	876	860
Q3	856,824	1,164	1,907	1,495	1,478
Q4	716,097	1,913	3,640	2,576	2,528
Q5	407,464	3,644	106,400	8,085	5,269
Total	3,899,160	24	106,400	1,959	1,190

(1) Amount of income in US$

Table 2
Income per quintile with 3 imputed bases (1)

Quintile	Number of Homes	Minimum	Maximum	Mean	Median
Q1	979,042	24	648	407	420
Q2	938,740	646	1,180	892	880
Q3	877,915	1,176	1,960	1,523	1,500
Q4	713,414	1,941	3,736	2,672	2,605
Q5	401,465	3,727	106,600	8,386	5,531
Total	3,910,576	24	106,600	2,006	1,200

(1) Amount of income in US$

In order to minimize the impact of missing data[3], a method of data imputation is used to replace missing values with imputed data[4]. All statistics and tests are performed on a non-imputed dataset and by combining the results obtained from three and five imputed datasets, with similar results in all cases.

To analyze the differences between different income levels, the sample is divided into income quintiles. As can be seen in tables 1 and 2, group Q1 includes homes with the lowest levels of income, while Q5 contains those with the highest sampled incomes[5].

Using the available data and survey questions format, we define "default" in the following way[6]:

- Mortgage default: The information for this classification is obtained from the survey question: "Are you up to date with your mortgage payment?" A family is considered to be in mortgage debt default if the head of the household replies the he (or she) is delinquent in his (her) payments or has stopped them altogether.

- Consumer default: A family that declares not to have outstanding mortgage debt, but declares itself delinquent in payments of consumer ("all purpose") loans (credit cards, department store credit cards, bank consumer loans, car loans or other forms of consumer related debt). In this case, the survey question considered is: "Approximately, in the last 12 months and for each outstanding form of debt, how many times have your credit payments fallen into delinquency?" We define default as payments that are late by the standards set in the contract of each form of debt. Unfortunately, the answers to this question do not allow us to distinguish which debt a household has defaulted on if it has both types of debt. This problem in the 2007 version of the EFH survey has been corrected, and the groups are properly identified as of the 2009 wave. We therefore study consumer debt default in a subsample of homes without mortgage debt.

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[3] Respondents who cannot or will not answer certain questions.

[4] Specifically, the EM/DA algorithm is used (expectation maximization / data augmentation). This process is repeated to generate ten imputed datasets. Averaging statistics and running models over various imputed datasets ensures that results and inferences gleaned from one set are stable and can be generalized in population. For details see Alfaro and Fuenzalida (2008).

[5] Appendix A.1 contains the description of each quintile for five imputed datasets.

[6] For further details, see *Cuestionario EFH 2007*, available at the Central Bank of Chile web site, www.bcentral.cl.

Table 3
Debt per quintile.

	Amount of Debt (1)			Numbers of Homes with Debt (2)			Average Debt (3)			Percent of Total Debt (4)		
N° of imputed datasets	0	3	5	0	3	5	0	3	5	0	3	5
Panel A: All household debt												
Q1	1,244	1,364	1,339	472,237	529,076	528,407	2,634	2,578	2,534	5	5	5
Q2	3,666	3,446	3,542	616,369	689,341	693,094	5,948	4,998	5,110	14	12	12
Q3	4,864	5,695	5,633	547,038	631,239	627,489	8,892	9,022	8,978	18	20	19
Q4	8,136	8,831	8,805	478,937	532,775	532,550	16,987	16,575	16,534	30	30	30
Q5	8,824	9,734	9,710	246,703	284,921	285,811	35,767	34,164	33,972	33	33	33
Total	26,734	29,070	29,029	2,361,284	2,667,351	2,667,351	70,228	67,339	67,127			
Panel B: Mortgage debt												
Q1	529	601	581	44,726	51,773	52,268	11,830	11,109	11,109	2	2	2
Q2	1,404	1,418	1,400	106,401	112,135	110,973	13,199	12,618	12,618	5	5	5
Q3	2,407	2,755	2,676	109,793	131,667	130,002	21,926	20,582	20,582	9	9	9
Q4	4,212	3,914	4,027	146,478	149,581	151,455	28,754	26,590	26,590	16	13	14
Q5	5,828	6,049	6,019	102,393	115,501	115,959	56,916	51,903	51,903	22	21	21
Total	14,381	14,738	14,702	509,791	560,657	560,657	132,626	122,801	122,801			
Panel C: Consumer debt												
Q1	688	733	728	453,357	505,673	505,004	1,519	1,450	1,442	3	3	3
Q2	2,132	1,884	1,997	586,597	651,374	655,043	3,634	2,892	3,048	8	6	7
Q3	2,224	2,694	2,698	509,398	588,885	585,166	4,366	4,575	4,610	8	9	9
Q4	3,649	4,569	4,431	438,702	484,237	483,910	8,317	9,436	9,156	14	16	15
Q5	2,719	3,355	3,375	216,555	248,194	249,240	12,554	13,517	13,539	10	12	12
Total	11,412	13,235	13,228	2,204,609	2,478,362	2,478,362	30,390	31,870	31,796			
Panel D: Consumer debt without mortgage debt												
Q1	621	593	592	420,044	435,955	434,843	1,478	1,361	1,361	2	2	2
Q2	1,911	1,472	1,596	498,303	521,633	526,008	3,835	2,821	3,034	7	5	5
Q3	1,726	1,764	1,778	411,408	429,418	427,380	4,195	4,108	4,160	6	6	6
Q4	2,494	3,192	3,032	318,912	322,231	320,581	7,820	9,907	9,457	9	11	10
Q5	1,543	1,675	1,704	132,742	136,639	137,064	11,622	12,259	12,435	6	6	6
Total	8,294	8,697	8,701	1,781,409	1,845,876	1,845,876	28,950	30,457	30,446			

(1) Amount of debt in US$ million

(2) Number of homes reporting outstanding debt.

(3) Average amount of debt per quintile in US$.

(4) Percentage of quintile amount of debt versus total debt.

In table 3, panel A shows total debt per income quintile, while panels B and C report results that contemplate mortgage and consumer debt respectively. Since there is an overlap in the sample of families that report having both mortgage and consumer debt, Panel D summarizes the data for consumer debt for families without mortgage debt. All statistics are estimated using imputation levels 0, 3 and 5. Results are qualitatively the same for all sets of imputations, and therefore the descriptions that follow apply to all.

As we can see in table 3, although Q5 represents a smaller number of homes than the others, the group represents a large portion of the total outstanding debt.

Table 4
Defaulted debt (DD) per quintile.

	Amount of DD (1)			Number of Homes with DD (2)			Average DD (3)			Percent of Quintile of Debt (4)		
N° of imputed	0	3	5	0	3	5	0	3	5	0	3	5
Panel A: Mortgage debt												
Q1	198	179	181	17,075	18,428	18,630	11,581	9,698	9,732	19	17	17
Q2	141	160	153	9,231	11,248	10,441	15,263	14,253	14,610	13	15	15
Q3	264	291	296	18,770	19,547	20,152	14,067	14,875	14,685	25	28	28
Q4	207	180	180	6,256	6,055	6,055	33,070	29,772	29,772	20	17	17
Q5	235	235	235	2,833	2,833	2,833	82,931	82,931	82,931	22	22	22
Total	1,045	1,045	1,045	54,165	58,111	58,111	156,912	151,528	151,730			
Panel B: Consumer debt without mortgage debt												
Q1	185	189	191	132,625	137,530	137,588	1,394	1,377	1,385	12	13	13
Q2	353	417	421	141,384	140,568	140,213	2,500	2,969	3,004	24	28	28
Q3	316	362	364	70,354	73,446	74,088	4,496	4,931	4,909	21	24	24
Q4	398	369	362	51,298	45,567	45,056	7,767	8,092	8,028	27	25	24
Q5	241	149	153	11,354	7,304	7,469	21,238	20,420	20,546	16	10	10
Total	1,494	1,487	1,491	407,015	404,415	404,415	37,394	37,789	37,873			

(1) Amount of defaulted debt in US$ million.

(2) Number of homes reporting defaulted debt.

(3) Average amount of defaulted debt per quintile in US$.

(4) Percentage of quintile amount defaulted debt versus total quintile debt.

By way of comparison, Q4 adds up to a comparable level of total debt, although Q4 represents nearly twice as many homes as Q5. In fact, as we can see in the case of five imputed datasets, the pattern of average debt per household is very stable, the level roughly doubling from one group to the next. When we split this analysis by types of debt we find that the pattern is very similar, in the sense that higher income quintiles have a larger portion of the population's total debt. However, this difference is more pronounced in mortgage debt, since lower income families have restricted access to this form of financing, and is almost nonexistent for families with consumer debt but no mortgage debt.

Table 4 contains the totals of defaulted debt per income quintile, both for mortgage debtors (panel A), and for consumer debtors without mortgage debt (panel B). Columns with analyses for different data imputations are as before.

In column 1 we see the levels of total defaulted debt for each quintile and each type of debt. It is interesting to note that the amounts of defaulted debt are similar across quintiles, while the number of homes with defaulted debt (in column 2) becomes smaller as the income level increases. In fact, as can be seen in column 4, the total amount of defaulted debt in the financial system is nearly evenly distributed between income quintiles. From table 1 we know that higher income quintiles have more debt outstanding, which means that the amount of defaulted debt as a percentage of outstanding debt per quintile (a measure of credit risk itself) also shows a monotonic decrease as the level of income increases. As an example, that ratio results in 38% of all mortgage debt being in default for Q1, while the same statistic for Q5 results in barely 4%.

What we see in this first analysis is in line with the main conclusion drawn by Fuenzalida and Ruiz-Tagle (2009), mainly that the larger portion of outstanding debt in Chile is in the hands of people with a relatively lower incidence of default.

4. Multivariate Analysis

4.1 Methodology

In order to study the determinants of household debt default we have to consider two choices of the households: having debt and being in default. In this way, we analyze two types of default equation: conditional on having debt and unconditional. For the latter we follow the literature on selection bias, in which our selection equation is the decision of the household to have debt.

Given the information available from the survey, we are able to perform both analyses for the case of mortgages but we have to restrict the conclusions for the case of consumer default. In the first case, we consider that the selection equation for default on mortgage is having this kind of debt, independent of having consumer debt. We note that in our sample of households with mortgages 83% of them also have consumer debt, which shows that most households have both kinds of debts. In addition to that we include as explanatory variable the DSR which includes all the monthly payments that households should pay. For the case of consumer default we consider only households without mortgage. We think that this constraint implies an interesting group of study given that consumer loans do not have collateral.

Considering the previous discussion we define X as a binary variable that takes the value one if the household reports debt and zero otherwise. For the case of default we use the variable Y which is equal to one if the household reports being in default, and zero otherwise. If we ignore the selection bias in the analysis of default we compute the Conditional Probability of Default (CPD) of the i-th household as follows

$$CPD_i = \Pr(Y_i = 1 \mid X_i = 1).$$

For the case of Unconditional Probability of Default (UPD) we use a first stage equation where the probability of having debt (PX) is defined for the i-th household as follows:

$$PX_i = \Pr(X_i = 1).$$

The second stage adjusts the CPD according with the effect of PX. Heckman (1979) shows that the two stage method is equivalent to solving the maximum likelihood multivariate normal approach. It is clear that the restriction of normality is strong, for which reason researchers tend to prefer the use of two stage methods. The key condition of this method is that the effect of the parameters from the first stage in the second stage be non-linear. In the case of the multivariate normal this non-linearity comes from the truncated distribution and it is a function of the density and the cumulative distribution functions.

Keeping in mind this mechanism we follow the empirical approach in this area (see, for example, Vella, 1998; Angrist 2001b) which relies on the use of non-linear functions of the probability computed in the fist stage, which in our case is represented by PX. In this way the effect of the first stage on second equation of the i–th household is represented by $g_i = g(PX_i)$, where g() is the logistic transformation we also include it's square in the second stage equation. Specifications with higher order expression of this transformation showed non significant effects on the explanatory variables nor in the overall effect. It is important to note that empirical applications tend to use polynomials of PX including higher order terms which are considered in our case given the non-linearity of the logistic function.

In addition to the inclusion of non-linear transformation of PX it is necessary to adjust the standard errors appropriately. Because we are using weights in the estimation we report the standard errors obtained by a bootstrapping procedure with 2000 replications. The results show that these standard errors are sometimes far bigger than the ones obtained by the standard method. That could be explained by the use of weights which are not included in the sampling procedure. In light of this we consider that a variable is significant at a higher level instead of the usual 5% or 10%.

Also, for the case of the probability function we consider the probit model. Results using the logit function do not change qualitatively; however, those are not reported in this paper. The use of a non-parametric probability functions is outside the scope of this paper and could be considered in future extensions of this research given the limitations of logit and probit models.

Finally, and just as important, we use both raw and imputed data. As we discussed in section 3, the missing information in the EFH was augmented by Multiple Imputation. In short, this means that for each missing value several possible values are provided in order to mimic the distribution of this variable that is consistent with the multivariate distribution of the whole survey. In other words, the original dataset with missing values is transformed into several datasets with full information in which each missing value is replaced by simulated values. Rubin (1987) and Schafer (1997) suggest performing tests with the combination of a few of the imputed datasets to reduce the variance of the estimates. Following this advice, we test the model using 3 and 5 imputed datasets, the results of the latter being reported in the appendices. We note that results are similar to the ones obtained using the raw data.

4.2 Mortgage Debt Default

As can be seen in tables 5 and 6, which show the estimates for mortgage debtors, whether analyzing the CPD or UPD, the results do not change significantly, as is also the case when including imputed datasets.

The effect of income in the PD has the expected sign and is also robust, whether expressed as a continuous variable or as quintile groups. The interpretation of the coefficients follows intuition:

the higher the total family income, the lower the probability that the family will default on its mortgage debt.

In Chile, access to bank accounts is far from universal and, recent market expansion notwithstanding, having one is still a sign that the user has a minimum income level (with all the related benefits of access to credit at better rates and terms). As stated in Morales and Yáñez (2006), in 2006 there were a little over 1.5 million checking accounts in Chile, indicating that only about 15% of the country's workforce had access to one . In terms of income cutoff, most banks consider a person to be eligible to open a bank account if his/her income is at or above CLP 400,000, which the EFH2007 shows to be the median income in Chile. We therefore control for such a borrower who has a bank account as an indicator of his/her socioeconomic status, as well as his/her relative access to credit (and the characteristics of this credit). Since banks apply their own credit and background checks, filters and models, a person that has a bank account can generally be expected to be at lower risk of default than someone who does not, all else being equal. Our results show that having a bank account is a significant and robust component of the PD.

Education is also an important and robust component of CPD and UPD specifications and tests with imputed dataset. Education is correlated with income and, therefore, one can expect that a higher level of education implies a higher income, which itself is conducent to a lower level of default risk. Also, the level of education is sometimes included in banks' evaluation of an individual's credit worthiness, and can therefore constitute a barrier to obtaining mortgage loans.

In this way, having a higher level of education is a personal characteristic that both provides access to mortgage debt, and characterizes the debtor as a relatively lower risk investment than a comparable person without the education credentials. Since this "bank filter" is not a factor for consumer (i.e.: non-securitized) debt, this variable is not significant in those regressions, as we will be seen below.

Gender of the person who contributes the highest amount to the family income has no significant effect on the probability of mortgage default. Marital status does not have an effect on the PD

Table 5
Probit estimations of mortgage default (1) (2)

Variable	Imp=0									
	No selection bias correction					Selection bias correction				
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 1	Model 2	Model 3	Model 4	Model 5
Gender (1 if male)	-0.0633			0.0749		-0.4875			-0.2626	
	(0.2666)			(0.2632)		(0.3267)			(0.3059)	
	[0.3017]			[0.3135]		[0.3305]			[0.3298]	
Married	-0.1772			-0.1928		0.4877			0.5103	
	(0.2747)			(0.2675)		(0.3467)			(0.3628)	
	[0.3253]			[0.3182]		[0.4062]			[0.4847]	
Age	0.083			0.0876		0.1607			0.1581	
	(0.0874)			(0.0849)		(0.1105)			(0.1063)	
	[0.119]			[0.1251]		[0.1321]			[0.1803]	
Age (squared)	-0.0008			-0.0009		-0.0012			-0.0013	
	(0.0009)			(0.0009)		(0.0012)			(0.0012)	
	[0.0012]			[0.0013]		[0.0016]			[0.002]	
High school	-1.0819	-0.9372	-0.9718	-1.1027	-0.9139	-0.3728	-0.8827	-0.7101	-0.3161	-0.5522
	(0.4146)	(0.4256)	(0.4130)	(0.3978)	(0.4005)	(0.3970)	(0.4706)	(0.4277)	(0.3717)	(0.4114)
	[0.6768]	[0.7413]	[0.7271]	[0.6281]	[0.715]	[0.5173]	[1.4486]	[1.3934]	[1.348]	[1.5282]
College	-1.0856	-1.0732	-0.9132	-0.9810	-0.7429	-0.5433	-1.1077	-0.8039	-0.4122	-0.5956
	(0.4128)	(0.4271)	(0.4217)	(0.4174)	(0.4077)	(0.4175)	(0.4878)	(0.4375)	(0.4090)	(0.4291)
	[0.6731]	[0.7446]	[0.7325]	[0.6579]	[0.7207]	[0.5231]	[1.4693]	[1.4015]	[1.373]	[1.5535]
Bank account	-0.3694	-0.6023	-0.301	-0.5041	-0.5634	-0.4020	-0.6948	-0.4386	-0.6847	-0.6847
	(0.2742)	(0.2489)	(0.2682)	(0.2628)	(0.2508)	(0.2478)	(0.2504)	(0.2569)	(0.2322)	(0.2412)
	[0.3339]	[0.275]	[0.3117]	[0.3361]	[0.2875]	[0.2591]	[0.297]	[0.3011]	[0.3159]	[0.2972]
Total income (log)	-0.3044		-0.4091			-0.5471		-0.3861		
	(0.1643)		(0.1890)			(0.2228)		(0.1975)		
	[0.1915]		[0.2064]			[0.2829]		[0.2214]		
DSR	0.3737	0.6015		0.3307	0.321	-0.0589	0.3121		-0.2602	0.0294
	(0.2663)	(0.3158)		(0.2622)	(0.2636)	(0.2947)	(0.2288)		(0.3544)	(0.2365)
	[0.429]	[0.4512]		[0.4631]	[0.4176]	[0.5985]	[0.3862]		[0.4874]	[0.3691]
LTV	-0.0971			-0.0443		0.0921			0.0813	
	(0.2449)			(0.2300)		(0.0448)			(0.0522)	
	[0.3246]			[0.3485]		[0.1079]			[0.1847]	
PX (logit)						0.5071	0.4405	0.3463	0.4735	0.3961
						(0.2605)	(0.1826)	(0.1594)	(0.2496)	(0.1772)
						[0.3800]	[0.2414]	[0.2322]	[0.3559]	[0.2674]
PX (logit-squared)						-0.0941	-0.2018	-0.1761	-0.0938	-0.1961
						(0.0747)	(0.0803)	(0.0731)	(0.0719)	(0.0797)
						[0.0835]	[0.1017]	[0.0953]	[0.0855]	[0.1064]
Quintile_dummies	No	No	No	Yes	Yes	No	No	No	Yes	Yes
Constant	1.916	-0.3684	5.2210	-1.4807	0.3378	1.4735	-0.5045	4.5719	-4.4354	0.2702
	(3.0245)	(0.4099)	(2.4822)	(2.0359)	(0.4587)	(4.0680)	(0.4309)	(2.6741)	(2.5715)	(0.5186)
	[4.021]	[0.7493]	[2.7957]	[3.0768]	[0.9144]	[4.8482]	[1.4286]	[3.3937]	[4.732]	[1.757]
Number of obs. (unweighted)	522	548	548	522	548	599	651	651	599	651
AIC (3)	355.440	355.930	353.630	360.040	360.340	266.140	287.490	282.590	255.480	275.650
BIC	308.600	334.400	332.090	300.430	321.580	323.280	318.840	313.940	325.810	324.920
Chi2				12.8**	12.5**				17.18***	12.48**

(1) The probit regressions are run on samples composed of a non-imputed dataset (Imp=0).

(2) The first number indicates the coefficient, the second, in parenthesis, the standard error and the third, in brackets, the bootstrapped standard error.

(3) AIC and BIC are Akaike and Schwarz information criteria, respectively.

Table 6
Probit estimations of mortgage default (1) (2)

Variable	Imp=3									
	No selection bias correction					Selection bias correction				
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 1	Model 2	Model 3	Model 4	Model 5
Gender (1 if male)	-0.0884			0.0110		-0.1031			0.0000	
	(0.2640)			(0.2808)		(0.2757)			(0.2889)	
	[0.2975]			[0.3193]		[0.3267]			[0.3419]	
Married	-0.2083			-0.2268		-0.0815			-0.0059	
	(0.2658)			(0.2663)		(0.2849)			(0.2894)	
	[0.3008]			[0.3179]		[0.3538]			[0.3747]	
Age	0.0760			0.0852		-0.0188			0.0406	
	(0.0749)			(0.0740)		(0.0963)			(0.1012)	
	[0.1015]			[0.1054]		[0.1354]			[0.1395]	
Age (squared)	-0.0007			-0.0009		0.0005			-0.0001	
	(0.0008)			(0.0008)		(0.0011)			(0.0011)	
	[0.0011]			[0.0011]		[0.0015]			[0.0015]	
High school	-1.1435	-1.0377	-1.0309	-1.1659	-0.9967	-0.6667	-0.9768	-0.8969	-0.6235	-0.7868
	(0.4124)	(0.4191)	(0.4126)	(0.4048)	(0.4019)	(0.4250)	(0.4263)	(0.4293)	(0.4059)	(0.4258)
	[0.7595]	[0.6711]	[0.7115]	[0.7369]	[0.6824]	[0.9708]	[0.9243]	[1.0375]	[0.9711]	[1.0319]
College	-1.0085	-1.0015	-0.8422	-0.9135	-0.6919	-0.5928	-1.0468	-0.8184	-0.5284	-0.6552
	(0.4126)	(0.4231)	(0.4151)	(0.4136)	(0.4082)	(0.4526)	(0.4302)	(0.4393)	(0.4165)	(0.4372)
	[0.7565]	[0.6748]	[0.7183]	[0.7403]	[0.6845]	[0.9740]	[0.9311]	[1.0522]	[0.9784]	[1.0448]
Bank account	-0.3294	-0.6336	-0.3205	-0.4705	-0.5204	-0.4356	-0.6734	-0.4377	-0.6476	-0.6408
	(0.2571)	(0.2393)	(0.2610)	(0.2528)	(0.2379)	(0.2553)	(0.2386)	(0.2521)	(0.2569)	(0.2390)
	[0.2974]	[0.2581]	[0.2779]	[0.2990]	[0.2664]	[0.3110]	[0.2735]	[0.2853]	[0.3105]	[0.2779]
Total income (log)	-0.3769		-0.4321			-0.5148		-0.4453		
	(0.1670)		(0.1731)			(0.2213)		(0.2045)		
	[0.1943]		[0.1844]			[0.2545]		[0.2222]		
DSR	0.1723	0.4022		0.1798	0.1615	-0.0262	0.1603		-0.1104	-0.0294
	(0.2377)	(0.2642)		(0.2708)	(0.2705)	(0.2637)	(0.2105)		(0.2923)	(0.2509)
	[0.3827]	[0.3524]		[0.4106]	[0.3924]	[0.4131	[0.2861]		[0.4306]	[0.3247]
LTV	-0.0749			-0.0316		0.0010			0.0004	
	(0.2271)			(0.2082)		(0.0019)			(0.0021)	
	[0.2802]			[0.3192]		[0.1320]			[0.1418]	
PX (logit)						0.6519	0.515	0.5089	0.5029	0.4098
						(0.3561)	(0.2798)	(0.2738)	(0.3325)	(0.2604)
						[0.3779]	[0.3145]	[0.2769]	[0.3899]	[0.3118]
PX (logit-squared)						-0.1579	-0.1254	-0.1577	-0.0737	-0.1068
						(0.0913)	(0.0953)	(0.0810)	(0.0922)	(0.0824)
						[0.0894]	[0.0929]	[0.0773]	[0.0972]	[0.0899]
Quintile_dummies	No	No	No	Yes	Yes	No	No	No	Yes	Yes
Constant	3.2168	-0.2801	5.5248	-1.3312	0.3579	5.7225	-0.6869	5.3043	-1.7786	0.1435
	(0.2853)	(0.4848)	(0.0158)	(0.4854)	(0.5171)	(3.6297)	(0.3790)	(2.6757)	(2.3934)	(0.5424)
	[3.8270]	[0.6639]	[2.5179]	[2.6902]	[0.8734]	[4.7231]	[0.8928]	[3.0715]	[3.582]	[1.3015]
Number of obs. (unweighted)	574	604	604	574	604	663	700	700	663	700

(1) The probit regressions are run on samples composed of three imputed datasets (Imp=3).

(2) The first number indicates the coefficient, the second, in parenthesis, the standard error and the third, in brackets, the bootstrapped standard error.

either. Pham et al. (2008) state that married couples seem to have a lower risk of mortgage default than single people. In the case studied by Pham et al. (2008) (rural Vietnam), husband and wife tend to have paid jobs, which constitutes a sort of diversification of risk in that, if one loses his or her source of income, the partner can temporarily help make up for the shortfall until the second income is restored. This mitigation of risk through diversification is a very significant result in their paper, although it does not seem to be a factor in our study. We believe that the effect of the number of people who actually contribute to the family income is more important than the marital status of the head of the family. For that reason we construct additional variables to control for there being more than one person who works in a given family, employed>1, as well as variables to separate the effects of having just two income earners in one home employed=2, versus having three or more people contributing to the household income employed>2. Tests with these variables show no interesting results, and we therefore do not reproduce them here. However, these variables do provide interesting information in the consumer debtors' case, which we discuss below.

Age and age squared are included to capture life cycle variations in behavior. These life cycle variables are not significant in almost any specification. This pattern follows the risk associated with increasing debt as a person ages and makes bigger investments (a larger family requires bigger home, and implies higher expenses), and then a decrease in risk as the debt is paid off and expenses reduced after a certain age peak.

We find that neither DSR nor LTV are significant for mortgage debtors. In the case of LTV, this could be due to the fact that the "value" component in the ratio is gleaned from an uninformed estimation (the actual question in the survey is "what do you think you would be paid if you sold your property today?"). We tested other sources of data to calculate the LTV ratio, such as the original purchase price of the property, the price the owner believes the property is worth, and the inflation-indexed original purchase price, but none of these definitions resulted in any meaningful contribution to the analysis. On the other hand, if this ratio is an indicator that the "benefit maximization" model of default decision is true, then not finding it a significant component of the PD confirms our intuition that the general public does not consider debt default as a strategic decision, but simply an unavoidable situation brought on by insolvency. Finally, both DSR and LTV are functionally related to income, as well as between each other, implying a high degree of multicolinearity.

4.3 Consumer Debt Default[7]

Tables 7 and 8 show the results of the models estimated to characterize consumer credit default. As with mortgage debtors, we find that the financial variables are robust in that they seem to be significant predictors of default in all specifications, whether we use the non-imputed dataset or any combination of imputed datasets, as well as CPD or UPD estimates. Income, whether it be a continuous variable or grouped by quintiles, is significant and its coefficient has a negative sign, indicating that the higher the level of a household's income, the lower its probability of falling into financial distress.

The coefficient for bank account is negative and significant and, although it is correlated with income, it does include an additional quality of having passed a bank's "due diligence" process, which certifies that the respondent has a minimum level of credit-worthiness.

With respect to the default theory "indicator" ratios, LTV is omitted from these regressions, since this ratio pertains to mortgage debtors only. On the other hand, DSR results are in line with expectations, that is, a positive coefficient, which is interpreted as the higher debt service compared to total income, the likelier it is for households to default. Nevertheless, DSR loses its significance when combining 3 and 5 imputed datasets for the analysis. We believe this is because DSR is calculated on the basis of total debt service and total income, both variables that are imputed to avoid missing values. Therefore, the instability inherent in the imputation process is inherited by the ratio and can thus render its coefficient insignificant.

The reason why DSR is significant for consumer credit debtors and not for mortgage debtors is that, as mentioned, DSR is correlated with income, since income is the denominator of the DSR ratio and, therefore, in the mortgage regressions, DSR is only significant when income is not present (and, in fact, the significance of income increases when DSR is not present). Unlike the

[7] Results shown here are based on Imp=0 and Imp=3. Probit estimates of consumer default with five imputed datasets can be found in Appendix A.3.

Table 7
Probit estimations of consumer default (1) (2)

Variable	Imp=0									
	No selection bias correction					Selection bias correction				
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 1	Model 2	Model 3	Model 4	Model 5
Gender (1 if male)	-0.0252					-0.1727				
	(0.1062)					(0.1193)				
	[0.1101]					[0.1615]				
Married	-0.103					-0.1872				
	(0.1023)					(0.1035)				
	[0.0831]					[0.0907]				
Age	0.0562	0.0503	0.0512	0.0503	0.0513	0.0678	0.0576	0.0594	0.0547	0.0566
	(0.0251)	(0.0247)	(0.0246)	(0.0244)	(0.0243)	(0.0274)	(0.0279)	(0.0275)	(0.0277)	(0.0274)
	[0.0202]	[0.0259]	[0.0255]	[0.0251]	[0.0253]	[0.0324]	[0.0284]	[0.029]	[0.028]	[0.0283]
Age (squared)	-0.0007	-0.0006	-0.0007	-0.0007	-0.0007	-0.0008	-0.0007	-0.0007	-0.0007	-0.0007
	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)
	[0.0002]	[0.0003]	[0.0003]	[0.0003]	[0.0003]	[0.0004]	[0.0003]	[0.0003]	[0.0003]	[0.0003]
Bank account	-0.4056	-0.4061	-0.3754	-0.4144	-0.3832	-0.2885	-0.2988	-0.2557	-0.3711	-0.3296
	(0.1429)	(0.1422)	(0.1402)	(0.1355)	(0.1340)	(0.1516)	(0.1505)	(0.1483)	(0.1429)	(0.1413)
	[0.1177]	[0.1468]	[0.1423]	[0.1425]	[0.1388]	[0.1765]	[0.1535]	[0.1568]	[0.1428]	[0.1463]
Total income (log)	-0.3859	-0.3968	-0.4151			-0.2447	-0.2789	-0.3113		
	(0.0792)	(0.0799)	(0.0811)			(0.0790)	(0.0802)	(0.0812)		
	[0.0703]	[0.0816]	[0.0825]			[0.079]	[0.0866]	[0.0881]		
DSR	0.2020	0.1961	0.1956	0.2074	0.2063	0.3070	0.3053	0.3122	0.3240	0.3308
	(0.1119)	(0.1109)	(0.1100)	(0.1089)	(0.1077)	(0.1211)	(0.1214)	(0.1218)	(0.1195)	(0.1196)
	[0.1119]	[0.1297]	[0.1268]	[0.1266]	[0.126]	[0.1612]	[0.1419]	[0.1435]	[0.1435]	[0.1486]
Employed>1 (3)	0.2813	0.2858		0.2691		0.3370	0.3496		0.3196	
	(0.1080)	(0.1082)		(0.1085)		(0.1083)	(0.1059)		(0.1066)	
	[0.1032]	[0.1078]		[0.11]		[0.0971]	[0.1087]		[0.1105]	
Employed=2 (4)			0.2433		0.2247			0.2794		0.2499
			(0.1135)		(0.1135)			(0.1133)		(0.1139)
			[0.1139]		[0.1173]			[0.1177]		[0.117]
Employed>2 (5)			0.4123		0.3991			0.5820		0.5494
			(0.1532)		(0.1549)			(0.1495)		(0.1500)
			[0.1553]		[0.1637]			[0.1568]		[0.1560]
PX (logit)						0.9632	0.9248	0.9289	0.9242	0.9256
						(0.1411)	(0.1388)	(0.1418)	(0.1386)	(0.1407)
						[0.2639]	[0.1786]	[0.1864]	[0.1895]	[0.1875]
PX (logit-squared)						-0.0964	-0.1163	-0.1112	-0.1146	-0.1083
						(0.1039)	(0.1026)	(0.1037)	(0.1043)	(0.1051)
						[0.1888]	[0.1262]	[0.128]	[0.131]	[0.1269]
Quintile_dummies	No	No	No	Yes	Yes	No	No	No	Yes	Yes
Constant	3.3097	3.5221	3.7293	-1.3738	-1.3952	0.3946	0.9153	1.2737	-2.4567	-2.4968
	(1.1208)	(1.1112)	(1.1322)	(0.5343)	(0.5321)	(1.0848)	(1.0752)	(1.1118)	(0.5940)	(0.5832)
	[1.1621]	[1.1537]	[1.1491]	[0.5498]	[0.5457]	[1.0214]	[1.1621]	[1.2311]	[0.6032]	[0.602]
Number of obs. (unweighted)	1659	1659	1659	1659	1659	2439	2439	2439	2439	2439
AIC (6)	1737.780	1725.370	1730.220	1753.430	1758.120	1678.020	1677.610	1677.290	1707.920	1707.800
BIC	1689.050	1687.480	1686.900	1699.290	1698.570	1614.230	1625.410	1619.300	1638.330	1632.410
Chi2				22.8***	23.9***				13.02***	15.36***

(1) The probit regressions are run on samples composed of a non-imputed dataset (Imp=0).

(2) The first number indicates the coefficient, the second, in parenthesis, the standard error and the third, in brackets, the bootstrapped standard error.

(3) Two or more persons employed in the household.

(4) Two persons employed in the household.

(5) Three or more persons employed in the household.

(6) AIC and BIC are Akaike and Schwarz information criteria, respectively.

Table 8

Probit estimations of consumer default (1) (2)

Variable	Imp=3									
	No selection bias correction					Selection bias correction				
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 1	Model 2	Model 3	Model 4	Model 5
Gender (1 if male)	-0.0176					-0.2308				
	(0.1060)					(0.1227)				
	[0.1072]					[0.1607]				
Married	-0.0585					-0.1404				
	(0.1029)					(0.1063)				
	[0.1043]					[0.1083]				
Age	0.0501	0.0472	0.0472	0.0464	0.0464	0.0733	0.0665	0.0673	0.0652	0.0659
	(0.0225)	(0.0222)	(0.0222)	(0.0221)	(0.0221)	(0.0265)	(0.0269)	(0.0265)	(0.0269)	(0.0266)
	[0.0233]	[0.0234]	[0.0228]	[0.0229]	[0.0232]	[0.0277]	[0.0276]	[0.0272]	[0.0277]	[0.0273]
Age (squared)	-0.0006	-0.0006	-0.0006	-0.0006	-0.0006	-0.0009	-0.0008	-0.0008	-0.0008	-0.0008
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)
	[0.0002]	[0.0002]	[0.0002]	[0.0002]	[0.0002]	[0.0003]	[0.0003]	[0.0003]	[0.0003]	[0.0003]
Bank account	-0.4076	-0.4082	-0.3784	-0.4164	-0.3844	-0.4543	-0.4536	-0.4038	-0.4600	-0.4101
	(0.1425)	(0.1421)	(0.1403)	(0.1404)	(0.1395)	(0.1498)	(0.1508)	(0.1484)	(0.1506)	(0.1484)
	[0.1439]	[0.1431]	[0.1429]	[0.1453]	[0.1414]	[0.1528]	[0.1565]	[0.1554]	[0.1541]	[0.1556]
Total income (log)	-0.3736	-0.3791	-0.4060			-0.2434	-0.2775	-0.3215		
	(0.0841)	(0.0847)	(0.0840)			(0.0846)	(0.0855)	(0.0835)		
	[0.0857]	[0.0854]	[0.0839]			[0.0988]	[0.0941]	[0.0960]		
DSR	0.1903	0.1844	0.1847	0.1889	0.1887	0.2239	0.2144	0.2229	0.2155	0.2244
	(0.1416)	(0.1421)	(0.1391)	(0.1424)	-0.139	(0.1793)	(0.1852)	(0.1804)	(0.1859)	(0.1811)
	[0.1519]	[0.1531]	[0.148]	[0.1541]	[0.1518]	[0.1963]	[0.2049]	[0.1978]	[0.2021]	[0.2006]
Employed>1 (3)	0.2338	0.2343		0.2218		0.3356	0.3484		0.3259	
	(0.1085)	(0.1084)		-0.1081		(0.1067)	(0.1048)		-0.1052	
	[0.1094]	[0.1079]		[0.1082]		[0.1093]	[0.1066]		[0.1081]	
Employed=2 (4)			0.1804		0.1640			0.2653		0.2416
			(0.1136)		(0.1121)			(0.1129)		(0.1116)
			[0.1144]		[0.1140]			[0.1157]		[0.1132]
Employed>2 (5)			0.3903		0.3853			0.6145		0.5921
			(0.1538)		-0.1565			(0.1521)		(0.1567)
			[0.1534]		[0.1601]			[0.1584]		[0.1611]
PX (logit)						0.8148	0.8114	0.8184	0.7949	0.7989
						(0.1287)	(0.1356)	(0.1409)	(0.1327)	(0.1366)
						[0.1650]	[0.1664]	[0.1755]	[0.1626]	[0.1693]
PX (logit-squared)						-0.0200	-0.0494	-0.0482	-0.0392	-0.0368
						(0.0714)	(0.0725)	(0.0748)	(0.0716)	(0.0734)
						[0.0901]	[0.0879]	[0.0909]	[0.0865]	[0.0893]
Quintile_dummies	No	No	No	Yes	Yes	No	No	No	Yes	Yes
Constant	3.2769	3.3775	3.7174	-1.2848	-1.2787	0.1033	0.5396	1.0687	-2.8589	-2.8693
	(1.1793)	(1.1748)	(1.1613)	(0.4945)	(0.4927)	(1.1606)	(1.1502)	(1.1322)	(0.5853)	(0.5765)
	[1.1944]	[1.1941]	[1.1638]	[0.5097]	[0.5131]	[1.3497]	[1.282]	[1.2963]	[0.613]	[0.6029]
Number of obs. (unweighted)	1730	1730	1730	1730	1730	2383	2383	2383	2383	2383

(1) The probit regressions are run on samples composed of three imputed datasets (Imp=3).

(2) The first number indicates the coefficient, the second, in parenthesis, the standard error and the third, in brackets, the bootstrapped standard error.

(3) Two or more persons employed in the household.

(4) Two persons employed in the household.

(5) Three or more persons employed in the household.

case of mortgage debtors, total consumer debt (the numerator of the DSR ratio) is composed of debt that cannot be monitored by a bank, or aggregated as a whole. An example of this are department store "credit cards", which can only be used at the issuing store or a few partner businesses at most, are easily obtained (hardly credit checks are needed) and the debts incurred with one issuer are not "visible" to another, nor are they reported into the financial system. Other examples include bank credit cards and overdraft lines, loans from family and friends, etc. Since this is the case, the information obtained in the EFH survey, which allows the DSR ratio to be constructed, is not freely available in the financial system, which means that, depending on the composition of their debt, highly leveraged individuals can choose to incur additional debt and, therefore, DSR is not a close proxy for income as in the mortgage case, and thus is far less likely to be significant in determining the PD.

We now turn to the demographic variables used in previous research. As with the mortgage case, gender and marital status are insignificant.

The life cycle is significant and robust in all specifications, indicating that default risk in this case is sensitive to the changes in debt as a person ages. Based on the fitted coefficients in the table (for the CPD models), we estimate that the default risk peaks at around 42 years of age, after which is begins to slowly decline.

Unlike with mortgage debtors, the probability of default for consumer credit debtors does not seem to be affected by the level of education. This lends support to our view that a reason for it to be significant in the mortgage, or securitized debt, case is due to bank monitoring and access to credit criteria. Since consumer lending standards are far more lax than for mortgage lending, education does not provide the "accreditation" effect it does for mortgage debtors.

Finally, in order to ascertain the importance of the number of people who contribute to the total family income within a household, we test variables that indicate whether there is more than one income provider in the household, employed>1, and two variables to separate this "more than one" effect into "exactly two", employed=2, income providers and "three or more", employed>2.

The intuition behind these tests is, in part, the same as the justification given by Pham et al. (2008) for the significance of the marriage variable: there is a diversification of risk if there is more than one provider of income in the household. We also have a prior belief that the higher the number of people that contribute to the household income, the higher that income should be and, as we've seen, higher income tends to reduce the risk of default. We therefore expect the occupation controls to have negative coefficients. However, the results show coefficients which are significant and robust in every specification, but with a positive sign. We believe that this is the result of two unobserved effects: relative job security and the motivation for the number of people working in a household. In the lower income quintiles people tend to have a lower level of education and are therefore able to obtain work only at a non-professional (or unskilled) level. This means that they are the most vulnerable to macroeconomic shocks that impact labor, thus making their source of income more uncertain, and their debt more risky. On the other side of the spectrum, people in the higher quintiles tend to have professional jobs, and tend to have much lower probabilities of being laid off, a situation described in Fuenzalida and Ruiz-Tagle (2009) in their analysis of the probability of job loss gleaned from panel data. It is therefore not necessary for higher quintile families to have more members with paying jobs. On the other hand, due to the inequality in income distribution in Chile[8], a higher number of people working in the household does not imply a larger combined income than that of a single person in a higher income quintile, meaning that a relatively large number of people in a family who contribute to the total income is a necessity and probably equates to a barely adequate total income. This can be seen in the low and middle quintiles, where a comparatively large number of people contribute to the family income and help diversify the job-loss risk as well, but the families are nevertheless classified into these low income quintiles, and their default risk is comparatively high. These considerations make the positive coefficients obtained a logical result of the country's labor and income conditions.

[8] In 2000, the Gini coefficient for Chile was 0.53, lagging behind most OECD countries. Source: "OECD Economic Surveys: Chile 2010".

5. Threshold Probability of Default

5.1. Motivation.

As we have seen in the previous analysis, there are various variables that act as determinants in the probability that a household will default on its debt, including income and its proxies, as well as demographic data. In this section we wish to explore the resulting PD by estimating a representative threshold probability of default, TPD, and then analyzing this resulting TPD within the confines of our study, as well as by benchmarking it with similar measures obtained by other researchers.

5.2. Estimation procedure.

We estimate the TPD as that which minimizes the quadratic difference between the probability of being in default as estimated from the fitted models of the previous section and the actual proportion of households who report being in default, as obtained from the EFH data.

In order to benchmark the relevance of our TPDs, we compare our measures to those obtained on the basis of results from the work by F-RT. Although F-RT do not estimate TPDs, they consider a household to be financially stressed if their DSR ratio is at 75% and their margin is below 20%[9]. Therefore, in order to obtain a similarly computed measure we obtain the average values of the independent variables of the probit regression for the subsample of people whose margin is at or below 20%, with one exception: regardless of the data, we hold the DSR for each group at 75%, to represent F-RT's threshold, and proceed to estimate the resulting TPDs as described above.

As we wish to benchmark our results against those obtained by Fuenzalida and Ruiz-Tagle, 2009 (F-RT), we must consider models that contain the variable DSR and restrict the samples used to those households that report having a margin of less than 20%.

For the case of mortgage default, the sample of households that report having mortgage debt is relatively small, and the set of homes that report mortgage default is much smaller so that

[9] "For household h, the margin is computed as: Mh = Yh - DSh - Eh, where Y is household total income, DS is debt service, and E is household total expenditures". See Fuenzalida and Ruiz-Tagle (2009).

including the constraint that the margin must be below 20% means that the resulting sample does not have sufficient representativeness at the quintile level to make separate estimations possible.

Given these conditions, for mortgage debtors we choose model 2, being the most parsimonious of those that contain DSR, and for consumer debtors we study models 4 and 5, which are estimated including quintile variables, and thus allow the study of the TPD for each income quintile.

5.3. Results

For mortgage debtors we obtain a value of TPD of 17% for CPD, meaning that for the whole sample of families with mortgage debt, having a probability of default above 17% should mean that they are in default. On the other hand, $TPD_{F\text{-}RT}$ is lower, at 15%. Estimated total debt in default for the measures of TPD and $TPD_{F\text{-}RT}$ are very close, at 11% and 12% of the total outstanding debt respectively.

In the case of consumer credit debtors the threshold is higher, located around 26% on average, as can be observed in table 9. The TPDs for CPD and UPD are similar for the upper quintiles, with small differences in the lower quintiles. Predicted amounts of debt in default range from 49% for the lowest income quintile, to only 12% for the highest income quintile.

Table 9
Threshold probability of default (TPD) consumer debt
(percentage)

	Model 4				Model 5			
	TPD		TPD F - RT (1)		TPD		TPD F - RT (1)	
Selection bias correction	No	Yes	No	Yes	No	Yes	No	Yes
Quintile 1	36	35	38	37	36	35	38	37
Quintile 2	37	37	32	33	37	38	34	35
Quintile 3	23	27	19	24	22	23	19	21
Quintile 4	23	28	19	22	23	30	19	19
Quintile 5	13	18	11	15	14	18	11	13

(1) Threshold probability of default based on parameters from Fuenzalida and Ruiz Tagle (2009).

As could be expected, the TPDs decrease monotonically as the income in each group increases, following the trends exhibited by the income variables used in the previous section. Also, the results are robust to the choice of model and the use of bias correction.

We can also see that, although the way F-RT perform their analysis is very different from the way we performed ours, the estimated TPDs are very close in every case. However F-RT's TPDs are almost invariably more strenuous than ours (a lower TPD means that more households are expected to be in default), indicating that families are more likely to fall into financial distress situations in their scenario. While we have performed a study on the information as a reflection of the real situation of families in 2007, F-RT perform a stress test based in a simulated shock that causes unemployment to rise in the economy, thus making default more likely. The results obtained here are thus consistent with their stressed scenario and further confirm the validity of our measure of default risk.

Finally, it is interesting to note that there is little difference in the TPD estimated for the first and second quintiles, as well as for those corresponding to the third and fourth quintiles. This is true whether we consider our own measures or those based on the work of F-RT. This observation would seem to indicate that, in terms of debt and default, the first two quintiles have a similar behavior, and could conceivably be studied as one group, as do the following two quintiles. This is consistent with the data as described in Section 3, where, for example, the number of homes that report defaulting on their debt is similar between quintiles 1 and 2, and quintiles 3 and 4, but there are important differences between these two groups and between them and quintile 5.

6. Conclusions

In the present paper, we study the determinants of debt default at the household level in Chile, using data obtained from the Survey of Household Finances performed in 2007. We find that the main determinants of mortgage debt default are income, and proxies of income such as income quintile indicator variables, having a bank account and even an education level beyond high school. In the case of consumer debt, we find that the main determinants are also income and related variables, but we also find statistical support for the DSR as well as for the number of people in the household who contribute to the total income.

We then estimate TPDs for both cases, mortgage and consumer debt, and compare them to the stressed scenario studied in F-RT. We find that in most cases the F-RT TPDs are close, though more strenuous than our estimations, indicating that families are likelier to fall in default in their scenario. Since our tests use data from the actual situation of families in 2007, F-RT run a stress test to estimate the consequences of macroeconomic shocks to labor in the household default levels of the Chilean economy, families are more likely to default in their study. The results obtained here are thus consistent with their stressed scenario, and further confirm the validity of our measure of default risk.

The results shown here open up new avenues for research in the areas of household finance and aggregate financial stability. The variables used in the analyses are for the most part drawn from the existing literature, so it is interesting to note and worthwhile to investigate why some results are consistent with those obtained in other countries, while others are not apparent, or even significant but contrary to expectations. Future research can also hope to develop from further instances of the EFH, when a panel study will be possible.

Finally, although F-RT have taken a first step, there are various forms of stress testing that can be applied to this data to better understand the possible effects of various changes in the prevalent market conditions, and how these might affect the stability of the Chilean financial system. Given the risks involved, the results of these tests might have important policy implications in terms of lending practices, credit scoring and screening.

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Appendix

A.1 Income per quintile with five imputed dataset

Table A.1

Income per quintile with 5 imputed bases (1)

Quintile	Number of Homes	Minimum	Maximum	Mean	Median
Q1	975,684	24	650	407	420
Q2	944,000	646	1,180	892	880
Q3	872,574	1,176	1,960	1,522	1,500
Q4	713,310	1,941	3,736	2,671	2,602
Q5	405,009	3,727	108,200	8,349	5,533
Total	3,910,576	24	108,200	2,009	1,200

(1) Amount of income in US$

A.2 Probit estimations of mortgage with five imputed dataset

Table A.2

Probit estimations of mortgage default (1) (2)

Variable	Imp=5									
	No selection bias correction					Selection bias correction				
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 1	Model 2	Model 3	Model 4	Model 5
Gender (1 if male)	-0.0829			0.0327		-0.0993			0.0291	
	(0.2625)			(0.2670)		(0.2742)			(0.2714)	
	[0.2941]			[0.3089]		[0.3265]			[0.3329]	
Married	-0.2107			-0.2266		-0.0825			-0.0045	
	(0.2638)			(0.2642)		(0.2846)			(0.2880)	
	[0.2989]			[0.3151]		[0.3472]			[0.3584]	
Age	0.0751			0.0875		-0.0201			0.0405	
	(0.0752)			(0.0754)		(0.0970)			(0.1019)	
	[0.1018]			[0.1079]		[0.1364]			[0.1434]	
Age (squared)	-0.0007			-0.0009		0.0005			-0.0001	
	(0.0008)			(0.0008)		(0.0011)			(0.0011)	
	[0.0011]			[0.0012]		[0.0015]			[0.0016]	
High school	-1.1545	-1.0533	-1.0351	-1.1844	-1.0074	-0.6699	-0.9806	-0.8968	-0.6156	-0.7766
	(0.4111)	(0.4168)	(0.4126)	(0.3992)	-0.4002	(0.4266)	(0.4262)	(0.4302)	(0.4082)	(0.4302)
	[0.7739]	[0.6759]	[0.7237]	[0.7295]	[0.6584]	[0.9840]	[0.9520]	[0.9445]	[1.0151]	[0.9719]
College	-1.0065	-1.0126	-0.8408	-0.8943	-0.6699	-0.5877	-1.0457	-0.8127	-0.488	-0.6187
	(0.4109)	(0.4216)	(0.4150)	(0.4079)	(0.3996)	(0.4521)	(0.4306)	(0.4396)	(0.4072)	(0.4314)
	[0.7727]	[0.6816]	[0.7278]	[0.7328]	[0.6609]	[0.9908]	[0.9602]	[0.9501]	[1.0158]	[0.9792]
Bank account	-0.3193	-0.6184	-0.3215	-0.4854	-0.5312	-0.4394	-0.6794	-0.4343	-0.6726	-0.6588
	(0.2670)	(0.2485)	(0.2598)	(0.2615)	(0.2466)	(0.2568)	(0.2405)	(0.2516)	(0.2581)	(0.2398)
	[0.3119]	[0.2712]	[0.2815]	[0.3137]	[0.2751]	[0.3085]	[0.2720]	[0.2805]	[0.3147]	[0.2762]
Total income (log)	-0.3927		-0.4361			-0.5229		-0.456		
	(0.1685)		(0.1718)			(0.2198)		(0.2044)		
	[0.1908]		[0.1850]			[0.2574]		[0.2170]		
DSR	0.1331	0.2943		0.1112	0.0974	-0.012	0.171		-0.1331	-0.0478
	(0.2532)	(0.3093)		(0.2441)	(0.2375)	(0.3095)	(0.2296)		(0.3321)	(0.2778)
	[0.4003]	[0.4047]		[0.4134]	[0.3819]	[0.4472]	[0.3003]		[0.4645]	[0.361]
LTV	-0.0941			-0.0424		0.0011			0.0004	
	(0.2348)			(0.2206)		(0.0019)			(0.0021)	
	[0.2953]			[0.3301]		[0.1346]			[0.1484]	
PX (logit)						0.6453	0.5136	0.5046	0.4939	0.4027
						(0.3588)	(0.2805)	(0.2743)	(0.3271)	(0.2588)
						[0.3600]	[0.3126]	[0.2792]	[0.3845]	[0.3219]
PX (logit-squared)						-0.1571	-0.1256	-0.1570	-0.0741	-0.107
						(0.0919)	(0.0955)	(0.0814)	(0.0907)	(0.0816)
						[0.0875]	[0.0926]	[0.0782]	[0.0953]	[0.0924]
Quintile_dummies	No	No	No	Yes	Yes	No	No	No	Yes	Yes
Constant	3.4684	-0.2349	5.5776	-1.2511	0.4695	5.8538	-0.6871	5.4478	-1.669	0.2473
	(2.9802)	(0.4024)	(2.2650)	(1.7910)	(0.4535)	(3.6290)	(0.3789)	(2.6750)	(2.4392)	(0.4896)
	[3.7578]	[0.6716]	[2.5242]	[2.6963]	[0.8006]	[4.7177]	[0.9222]	[2.9758]	[3.6627]	[1.1292]
Number of obs. (unweighted)	574	604	604	574	604	663	700	700	663	700

(1) The probit regressions are run on samples composed of three imputed datasets (Imp=5).

(2) The first number indicates the coefficient, the second, in parenthesis, the standard error and the third, in brackets, the bootstrapped standard error.

A.3 Probit estimations of consumer with five imputed dataset

Table A.3
Probit estimations of consumer default (1) (2)

Variable	Imp=5									
	No selection bias correction					Selection bias correction				
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 1	Model 2	Model 3	Model 4	Model 5
Gender (1 if male)	-0.0172					-0.2296				
	(0.1060)					(0.1228)				
	[0.1069]					[0.1627]				
Married	-0.0562					-0.1393				
	(0.1030)					(0.1063)				
	[0.1033]					[0.1072]				
Age	0.0501	0.0473	0.0473	0.0466	0.0465	0.0736	0.0668	0.0675	0.0657	0.0664
	(0.0225)	(0.0222)	(0.0222)	(0.0221)	(0.0221)	(0.0265)	(0.0269)	(0.0265)	(0.0269)	(0.0266)
	[0.0233]	[0.0232]	[0.0226]	[0.0231]	[0.0225]	[0.0273]	[0.0275]	[0.0272]	[0.0274]	[0.0275]
Age (squared)	-0.0006	-0.0006	-0.0006	-0.0006	-0.0006	-0.0009	-0.0008	-0.0008	-0.0008	-0.0008
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)
	[0.0002]	[0.0002]	[0.0002]	[0.0002]	[0.0002]	[0.0003]	[0.0003]	[0.0003]	[0.0003]	[0.0003]
Bank account	-0.4029	-0.4035	-0.3736	-0.4134	-0.3816	-0.4495	-0.4490	-0.3987	-0.4566	-0.4064
	(0.1422)	(0.1418)	(0.1401)	(0.1395)	(0.1386)	(0.1491)	(0.1501)	(0.1478)	(0.1493)	(0.1474)
	[0.1440]	[0.1438]	[0.1417]	[0.1439]	[0.1408]	[0.1545]	[0.1542]	[0.1515]	[0.1524]	[0.1534]
Total income (log)	-0.3744	-0.3797	-0.4066			-0.2426	-0.2772	-0.3215		
	(0.0834)	(0.0841)	(0.0832)			(0.0841)	(0.0851)	(0.0828)		
	[0.0834]	[0.0853]	[0.0839]			[0.0976]	[0.0957]	[0.0944]		
DSR	0.1742	0.1688	0.1685	0.1744	0.1736	0.2145	0.2075	0.2164	0.2093	0.2185
	(0.1346)	(0.1344)	(0.1329)	(0.1335)	(0.1315)	(0.1590)	(0.1634)	(0.1608)	(0.1620)	(0.1593)
	[0.1493]	[0.1474]	[0.1452]	[0.1457]	[0.1438]	[0.1757]	[0.1797]	[0.1772]	[0.1796]	[0.1769]
Employed>1 (3)	0.2345	0.2350		0.2201		0.3376	0.3506		0.3271	
	(0.1080)	(0.1079)		(0.1083)		(0.1061)	(0.1042)		(0.1051)	
	[0.1077]	[0.1089]		[0.1081]		[0.1089]	[0.1078]		[0.1076]	
Employed=2 (4)			0.1814		0.1631			0.2675		0.2429
			(0.1132)		(0.1122)			(0.1124)		(0.1115)
			[0.1136]		[0.1113]			[0.1149]		[0.1137]
Employed>2 (5)			0.3903		0.3812			0.6174		0.5935
			(0.1533)		(0.1568)			(0.1515)		(0.1567)
			[0.1555]		[0.1577]			[0.1567]		[0.161]
PX (logit)						0.8129	0.8094	0.8163	0.7938	0.7977
						(0.1283)	(0.1352)	(0.1405)	(0.1322)	(0.1361)
						[0.1618]	[0.1675]	[0.1707]	[0.1625]	[0.1672]
PX (logit-squared)						-0.0185	-0.0477	-0.0464	-0.0374	-0.0348
						(0.0712)	(0.0724)	(0.0746)	(0.0714)	(0.0732)
						[0.0901]	[0.0872]	[0.0892]	[0.0863]	[0.0895]
Quintile_dummies	No	No	No	Yes	Yes	No	No	No	Yes	Yes
Constant	3.2873	3.3849	3.7246	-1.2811	-1.2744	0.0848	0.5267	1.0591	-2.8691	-2.8794
	(1.1706)	(1.1665)	(1.1503)	(0.4950)	(0.4933)	(1.1534)	(1.1450)	(1.1230)	(0.5861)	(0.5774)
	[1.1693]	[1.1843]	[1.1647]	[0.5137]	[0.5005]	[1.335]	[1.2885]	[1.2866]	[0.6037]	[0.6075]
Number of obs. (unweighted)	1730	1730	1730	1730	1730	2383	2383	2383	2383	2383

(1) The probit regressions are run on samples composed of five imputed datasets (Imp=5).

(2) The first number indicates the coefficient, the second, in parenthesis, the standard error and the third, in brackets, the bootstrapped standard error.

(3) Two or more persons employed in the household.

(4) Two persons employed in the household.

(5) Three or more persons employed in the household.

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