Measurement of Household Risk with the Survey of Household Finances

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The recent turmoil in household credit market has led to a growing literature that studies household debt as a source of systemic risk in the financial sector. Indeed, it is highly documented that the indebtedness has been increasing in absolute and relative terms in several economies during the last two decades. For some developed economies such as the U.S. and the U.K. household debt represents more than 100% of the GDP (see for instance Debelle, 2004; Girouard et al., 2006; Karasulu; 2008; and Ma et al., 2009). In specific for Chile the average growth rate of households' debt was 12.8% in real terms during the period 2000-09. Chilean household debt levels suffered a dip during the subprime crisis, the growth rate of household debt recovered to 7.5% and has surpassed the pre-crisis level of indebtedness, nearly over 60% of the GDP (Central Bank of Chile, 2010). The growth of indebtedness in the household sector is attributed to financial innovations, reduction of the level of credit and liquidity constraints, and decreases in nominal and real interest rates (Debelle, 2004).

A high level of indebtedness affects the economy by two channels, financial stability and monetary policy (see Debelle, 2004; Benito et al., 2007). In the first place, since the size of the households' indebtedness represents a large item in banks' balance sheets, high levels of indebtedness imply a greater exposure of financial institutions toward the household sector[1]. Thus, if the capability of the household to serve its debts is in doubt, then banks' losses on their loans to households could be significant, increasing the fragility of the entire financial system. In this view, May and Tudela (2005) introduce the concept "debt-at-risk" as an indicator of credit risk. The measure used the sum of housing debt multiplied by the household likelihood of financial distress. Herrala and Kauko (2007)

[1] Ma et al.(2009), using 2007 data, note that the share of household loans in total bank loans varies significantly across country, from 15% in China to 70% in Australia.

calculate this debt at risk for Finland using microdata and analyze whether bank loan losses or a financial crisis can be predicted.

Second, but not less important, are its effects on monetary policy. High levels of household indebtedness could make households more sensitive to economic shocks than otherwise. This is because high level of indebtedness could constrain households' access to credit, affecting its ability to smooth consumption over time. This fall in aggregate consumption affects the demand of goods and services, and therefore decreases economic growth. Besides, a higher household' indebtedness imposes a pressure on monetary policy, since an increase in the interest rate generates a rise in the debt burden, which exposes the household to a higher default probability and a reduction in the disposable income.

The purpose of this article is to distinguish the main determinants of default in the households' debt using a probit model. In the estimation we incorporate two novel variables: (i) a new financial indicator, a modify debt service ratio (MDSR) and (ii) the probability of layoff of household's head. The MDSR allows us to eliminate the outliers' problem in the traditional DSR and to include household even if its (transitory) income is zero, whereas the probability of layoffs incorporates in the estimation the uncertainty respect to the labour status and income of the household's head. Then we analyze the marginal effect of the MDSR on the probability of default conditional in the level of households' income and age of the households' head. Finally, we calculate the debt at risk in the Chilean households using the procedure developed in May and Tudela (2005).

To analyze the probability of default in the household level, we use the Survey of Household Finances (SHF) 2007, of the Central Bank of Chile, which reports information about the income, assets and debts of the household. Since we use the microdata of the SHF to estimate the probit model, we develop a bootstrap procedure to incorporate the multiple imputations and the population weights in the estimation process.

The article is organized as follows. In the first section we describe the debt service ratio (DSR), in the section II we describe a new financial index, the modify debt service ratio (MDSR). The section III compares the standard DSR with our new financial index (MDSR); section IV, we present the stimation process, whereas section V shows the stimation results. In section VI analyze the marginal probability of default contional in some characteristics of the sample and section VII shows the debt at risk. Section VIII concludes.

I. Debt Service Ratio Analysis

One of the most used indexes to describe household financial risk and its evolution across countries is the Debt Service to Income Ratio (DSR). It shows the percentage of households' income that is destined to pay their financial obligations. That is, if a household has a high DSR, it means that this household must spend a large fraction of its income in order to serve its debts. This index can be built using aggregate level data from national accounts or using microdata at the household level from surveys. However, aggregate data could hide valuable information about the distribution of the debts and the real size of the debt in risk. Hence, working with micro data presents great benefits for policy makers[2].

There are several recent papers that use microdata to study households' indebtedness. Most of them analyze how a financial index, like the DSR, is distributed across households and what factors affects their capability to meet their commitments[3]. One of the first papers that addresses the

[2] See ECB (2009).

[3] See May, Tudela and Young (2004), May and Tudela (2005) for the U.K.; Bucks et al. (2006) and Bucks et al. (2009) for the U.S., Johansson and Persson (2006) for the case of Sweden, Zochowski and Zajaczkowski (2006) for Poland; Cox, Parrado and Ruiz-Tagle (2006), Fuenzalida and Ruiz-Tagle (2009) for Chile; Herrala and Kauko (2007) for Finland; Faruqui (2008) for Canada; Karasulu (2008) for Korea; Albacete and Fessler (2010) for Austria, among others.

effectiveness of financial ratios as a predictor of household insolvency was DeVaney (1994)[4]. She finds that the DSR is useful as a predictor of household insolvency. Besides, since it is easily calculated for each family, it serves as a guideline to evaluate the level of debt that a household is able to manage relative to its income.

The functional form of the DSR is represented by:

$$DSR_h = \frac{db_h}{y_h},$$

where db_h is the debt burden and y_h the income of the household h. The debt burden of each household h is defined by:

$$db_h = \sum_{k \in h} \sum_{j \in J} f\left(M_{j,k}, p_{j,k}, r_{j,k}\right),$$

where $M_{j,k}$ is the amount of debt of type j (where j can be consumer debt, credit card debt, mortgage debt, and others) of the member k of the household h, $p_{j,k}$ is the term of the debt j of the member k of the household h, and $r_{j,k}$ is the interest rate of the debt j owned by member k of the household h. The debt burden is represented by the function $f(\cdot)$, which is increasing in $M_{j,k}$ and $r_{j,k}$, and decreasing in $p_{j,k}$.

The simplicity in its construction is the main characteristic of the DSR. However, this indicator is not exempt of problems. In fact, we state that the DSR presents two main problems: (i) poor treatment of outliers and low accuracy in the measures of central tendency and (ii) the removal of households without temporary income.

The first problem is referred to households with low income. Indeed, a household with debt burden and a relatively low income will have an extremely high DSR, affecting its distribution. In this literature, this problem does not have a standard solution. In some cases the DSR is censured in some point of its domain, whereas in others cases it is truncated in an arbitrary value. However, both alternatives have implications on the distribution of the DSR, which are not taken into account by researchers. In order to stress our points, we present in Table 1 a set of statistics for three alternative ways to present the DSR used in the literature. Panel 1 shows statistics of the standard DSR, panel 2 presents the DSR censored in 100%[5], panel 3 shows the DSR truncated in the median (as in Faruqui, 2008) and, panel 4 shows the standard DSR, but including households without any income. These households receive the maximum DSR level of the households with both debt and income in the sample. In order to focus our analysis in more risky households, we split the sample by three income strata. Stratum 1 represents the poorest households, which belongs to the first five deciles of household income. Stratum 2 brackets deciles 6, 7 and 8, while stratus 3 groups deciles 9 and 10.

The first problem is related to the censoring or truncation of the distribution of the DSR. Particularly, censoring the DSR affects mainly its central tendency measures, while truncating affects both the central tendency and dispersion measures of the distribution.

On the one hand, if we focus in panels 1 and 2 we see that the effect of censoring the DSR generates a moderate change in the dispersion measures of the distribution. It produces an increase of 74bp and 32bp in the median of stratum 1 and of the total households, respectively. The most important variation is produced in the mean and the standard deviation. The mean in stratum 1 decreases 439bp from 40% to 35%, meanwhile this change is 405 and 305bp for strata 2 and 3,

[4]The author use the following financial ratios: Liquid Asset/Disposable Income, Total Assets/Total Liabilities, Annual consumer Debt Payments/Disposable Income, Annual Shelter Costs/Total Income, Gross Annual Debt Payments/Disposable Income.

[5]This solution incorporates in the distribution households temporarily without income.

respectively. These changes affect the mean of the total households in around 400bp, which shows that the few households with DSR levels above 100% could affect more than 10% of the mean DSR. This huge effect of a few households on the mean DSR using the standard measures make its statistics too volatile and its mean hard or impossible to interpret. With regards to the standard deviation, it decreases in almost 3,800bp for total households, whereas across strata the reduction was to 5,119bp, 2,897bp and 1,832bp for strata 1,2 and 3, respectively.

On the other hand, comparing panel 1 and panel 3 let us see how the distribution is affected by truncating the DSR. Panel 3 shows that the mean is decreased approximately by a half throughout strata, and the standard deviation decreases in 5328bp for the total population of indebted households. In terms of uncentered moments, we can see that ignoring a DSR greater than 50% decreases the median around to 440bp in the total households, which implies a significant change respect to the standard DSR's median.

Therefore, the results in the table 1 show that the traditional solutions to outliers problem have important statistical consequences over the conclusions that we can extract from the distribution of the DSR. For this reason, it is important to move towards a measure that allows us to treat the outliers' problem without the arbitrariness of choosing some value for truncating or censoring the DSR.

Table 1: Characterization for Alternative DSR's Distribution.

		% Indebted households	Mean	Standard Deviation	Median	Interquartile Range	P 99
Panel 1	Total Households	63.28	34.18	66.51	19.61	31.81	193.75
Standard DSR	Stratum 1	54.57	40.13	83.30	21.86	36.25	191.49
	Stratum 2	71.35	30.61	53.97	18.75	28.26	193.75
	Stratum 3	73.04	28.27	42.39	17.05	26.14	219.43
Panel 2	Total Households	64.31	30.30	28.58	19.93	32.80	100
Censored DSR	Stratum 1	56.57	35.74	32.11	22.60	40.35	100
	Stratum 2	71.40	26.56	25.00	18.75	28.48	100
	Stratum 3	73.13	25.22	24.07	17.05	26.14	100
Panel 3	Total Households	52.20	18.41	13.23	15.21	20.20	48.61
Truncated DSR	Stratum 1	42.16	19.10	13.37	15.76	22.46	48.61
	Stratum 2	61.76	18.40	13.42	15.14	20.08	48.89
	Stratum 3	63.03	17.26	12.60	14.77	18.09	48.51
Panel 4	Total Households	64.31	63.85	241.05	19.93	32.80	1875.92
Standard DSR	Stratum 1	56.57	104.98	348.63	22.60	40.35	1875.92
with households	Stratum 2	71.40	32.09	75.07	18.75	28.48	245.39
without income	Stratum 3	73.13	30.53	77.15	17.05	26.14	221.07

Stratum 1, represents households that belongs to the first to fifth income deciles.

Stratum 2, represents households that belongs to the sixth to eighth income deciles.

Stratum 3, represents households that belongs to the ninth to tenth income deciles.

Source: Author's calculation

As we pointed above, the second problem is related to households without temporary income. In this case, given that their income is zero, the DSR for these households will be undefined. Therefore, the most financially distressed households are excluded from the analysis. This fact is not taken into account by the standard DSR. To figure out the dimension of this censoring, the last panel of table 1 includes all the households without income[6]. These households represent 1.6% of the total indebted

[6] The households temporarily without income are incorporated receiving the maximum standard DSR in the sample

households in the sample. In fact, a 3.5% of the households belonging to stratum 1 have zero income and also possess debts. In strata 2 and 3, these households amount to nearly 0.1%[7]. As noted in this table, the most important effect is concentrated in the measures of central tendency. For instance, it produces a significant increase in the mean of the DSR of 2,967bp for the total indebted households, with the greater changes in stratum 1 (6,485bp). This means that ignoring households without income leads us to underestimate the real level of risk in the household sector.

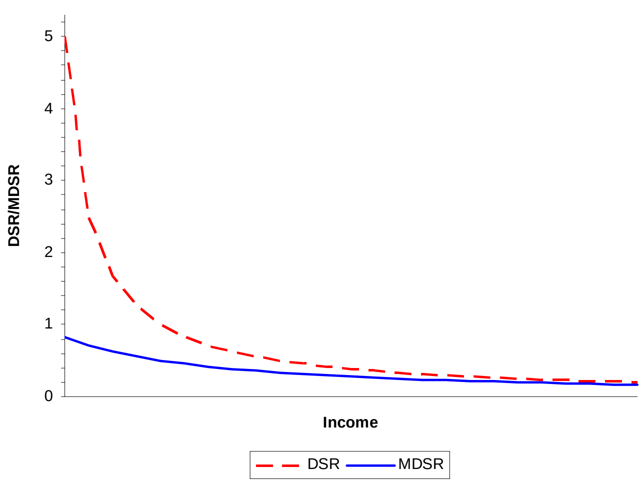
II. A New Financial Index: MDSR

In this section we introduce a new financial risk index. This new index is a modification of the standard DSR, which we call Modified Debt Services Ratio (MDSR). This transformation allows us to eliminate the problems presented in the standard DSR showed in the previous section. The proposed functional form is:

$$MDSR_h = \frac{db_h}{db_h + y_h},$$

where db_h and y_h are defined identically as the ones in the DSR. Two important things have to be noted. In first place, the interpretation of the MDSR is not as direct as well as the standard DSR, in the sense that it does not represent a proportion of the household's income destined to serve its debts. However, the main difference between those indexes is that our new index is bounded. Figure 1 clearly shows that the MDSR is not affected by extreme observations, whereas as household's income goes to zero the DSR converge to infinity. This fact allows us to include households that have low or non transitory income, without the need to impose an arbitrary upper value for the DSR, like when one truncate or censor the DSR. In deed, households with low income and even without any earnings, will always have a MDSR non greater than one. Thus, the MDSR let us to focus the analysis on those households with more liquidity problems and, therefore, with more probability to give default, which are not considered in the previous literature.

Figure 1: Income vs MDSR/DSR



Source: Author's calculation.

excluding them.

[7]It is important to note that when we add households without income, it increases the number of households for each strata. This is because income strata are predefined using actual income and income level of the city in which they live. Therefore it is possible for a household to be living in a wealthy city and to declare no income.

In order to show why the MDSR solves the other problems of the DSR, we present in the table 2 a characterization of the MDSR' distribution. Particularly, table 2 shows the same measures of table 1 and also, in parenthesis, it shows the corresponding value in terms of the DSR . The values shows that the magnitudes in the MDSR are very similar to that the DSR, but the stability presented in the MDSR generates that the tails of the distribution are well defined in the MDSR. Comparing the results in table 2 respect to table 1, we can see that the MDSR is relatively stable in the tail as the censored DSR. This pattern is not present in the others alternatives of DSR. The MDSR does not show an extreme sensibility in central measures to extreme observations as the DSR in panel 4 in table 1.

Table 2: Characterization of MDSR' distribution.

	% Indebted Households	Mean	Median	Interquartile	P 99
Total Households	64.31	21.53	16.62	21.27	100.00
		(27.44)	(19.93)	(27.02)	ind
Stratum 1	56.57	25.25	18.43	24.17	100.00
		(33.78)	(22.6)	(31.87)	ind
Stratum 2	71.40	18.90	15.79	19.27	71.05
		(23.31)	(18.75)	(23.86)	(245.39)
Stratum 3	73.13	18.18	14.56	18.01	68.85
		(22.21)	(17.05)	(21.97)	(221.07)

The numbers in parentheses represent the DSR equivalent value of the respective MDSR.
Source: Author's calculation

III. Relationship between the DSR and MDSR

In this section we establish the relation between the MDSR and DSR to facilitate the lecture and comparison of our results in the next section with the ones existing in the literature. One important characteristic of the MDSR is that can be expressed in terms of DSR in a very easy manner. In fact, the MDSR has a one to one mapping with the DSR, which is given by:

$$MDSR_h = \frac{DSR_h}{1 + DSR_h}.$$

To show the impact of our measure in the characterization of the household debt' distribution, table 3 shows how the debt is distributed in terms of the DSR and the MDSR by each DSR decil. We see that more than 50% of the households with debt are concentrated in a MDSR lower that 9.1% (10% in the DSR terms). However, this proportion of households has a relatively low participation in the total amount of the debt, representing only an 8%. In fact, more than 50% of the debt is concentrated in households with an MDSR level between 9.2% and 28.6%.

If we focus on the last line of the table 3, households with income lower than the debt burden correspond to 4.5%. These households are those that cause the problems in the tail of DSR and some of them are not even considered in the DSR, despite the fact that they are the most distressed households. These households mantain around 8% of the total debt and represent the 14% of the consumption debt, both amounts are significant. In fact, the proportion of the consumption debt in these household is the biggest through the MDSR.

In terms of the evolution of these households, as DeVaney (1994) points out, those households can not be liquidated, "the individual or family must continue to function as a social and economic unit". Therefore, those households have two options: (i) to try to pay their debts increasing their indebtedness (in the formal or informal market), or (ii) to file in bankruptcy. In the first option, the household continue acquiring debts thinking that their low income is only a transitory situation. The problem of this possibility is that households are holding their hopes in a highly uncertain situation, making even more delicate their financial status. In the second option, households cease to pay their financial obligations, and therefore, they must confront all the economic and social costs involved in the bankruptcy.

Table 3: ***Distribution of the Debts expressed in DSR and DSRM***

DSR	MDSR	% Indebted Households	Total Debt	Consumption Debt	Mortgage Debt
0 - 10	0 - 9.1	52.83	8.68	9.26	8.33
11 - 20	9.2 - 16.7	14.77	18.35	13.60	21.25
21 - 30	16.8 - 23.1	8.37	18.04	13.96	20.54
31 - 40	23.2 - 28.6	6.71	16.45	13.18	18.45
41 - 50	28.7 - 33.3	4.79	7.99	8.78	7.50
51 - 60	33.4 - 37.5	2.84	7.74	8.33	7.37
61 - 70	37.6 - 41.2	1.69	4.61	7.34	2.94
71 - 80	41.3 - 44.4	1.08	3.06	3.23	2.96
81 - 90	44.5 - 47.4	1.12	3.83	5.28	2.94
91 - 100	47.5 - 50	1.32	3.00	2.94	3.04
More than 100	More than 50	4.49	8.26	14.11	4.69
Total		100	100	100	100

Source: Author's calculation

IV. Probability of Default

In this section, we study the main determinants of the probability of default and use our new index MDSR in order to establish its importance as a measure for financial distress. Several articles try to study this relationship in a similar way, but without taking into account the problems present by the DSR, which, as we show, may have a significant effect on the results obtained. Other important aspect to consider is that we include another novel variable to the probit model, the probability of layoff, which tries to control by the uncertainty over expected income in the household. As it is noted in other papers, the level of unemployment is one of the biggest causes of the financial default (see for instance Fuenzalida y Ruiz-Tagle, 2009; La Cava and Simon, 2000). Therefore the inclusion of this variable would bring some new insight about how the unemployment status affects the probability of default. The variable is constructed using information from the ESI[8] 2007, checking it with the information from SFH. We assign to each household head the probability of layoff conditional on his working geographic zone, schooling and age.

To find a certain threshold for the MDSR, we include interaction variables that allow us to estimate different slopes for the MDSR, given two dummy variables with a lower and upper bound. We run a series of estimations changing marginally the lower and upper bounds for the MDSR. This allows us to detect some significant and statistical changes in the estimated parameter. Del-Río

[8]ESI (Encuesta Suplementaria de Ingresos) executed by National Statistical Institute, collects information about income and labour status of the household's head.

and Young (2005) used a similar procedure for British households, where they constructed several dummy variables for different levels of DSR[9]. Notwithstanding, they use a discrete variable rather than a continuous one in order to not impose a particular functional form, between the DSR and the probability of reporting debt problems. They do not found any threshold for the DSR, in fact, they found a monotonically increasing smooth relationship between the DSR and the probability of financial problems.

As we work with microdata that contain missing values and incorporate population weights, the estimation process is not trivial. The missing data can be solved using imputations methods (Shafer, 1997), which is the standard solution in the literature. However, to consider the population weights and multiple imputations in the estimation process is a hard task, because there is no analytical solution to estimate generate the standard errors correctly. To solve this problem we use a bootstrap procedure to carry out the estimation and calculate the standard errors, using both the population weights and the Rubin's rules for the variance of missing data (Shao and Sitter, 1996). This process is implemented in the following way. First, we generate a bootstrap sample of the households, calculate new expansion factors for all population strata, and estimate the mean coefficients over 30 imputed samples. Then we calculate the variance of the imputed estimation over all the 30 imputations and save both the mean coefficients and their variance over all the imputed samples. Finally, at the end of all bootstrap samples we estimate the variance of the coefficients as being the mean variance of the coefficients over all bootstrap replicas plus the mean variance of the imputations. The mean variance of the imputations is also estimated using all the bootstrap replicas. In this paper we used 1000 bootstrap replicas for the estimation.

In the estimation of default model, we focus our analysis on consumption debt. This decision was adopted due to several reasons. In the first place the percentage of household with consumption debt reach a 65% in the Chilean households, whereas the households with mortgage debt reach only a 20%. Also, consumption debt is seen as riskier than mortgage debt, because the mortgage debt is collateralized (Fuenzalida and Ruiz-Tagle, 2009) and the financial institutions do not lend the entire value of the house being purchased. This fact makes mortgage loans primarily concentrated in the most wealth percentiles of the population, and therefore, with more probability to be paid. In fact, only an 8% of the first income stratum possesses a mortgage debt, being 21% and 20%, for stratum 2 and stratum 3, respectively (see Central Bank of Chile, 2010). On the other hand, a considerable part of all income strata have consumption debt (58%, 71% and 64% for strata 1, 2, 3, respectively). Also, the government acts as a lender in the mortgage sector to lower income household, which implies that households of lower income are subsidized and do not draw on the financial sector to acquire mortgage debt.

To construct the dependent variable, we use data from the Survey Households Finances (SHF) 2007, executed by Central Bank of Chile. In particular, we use some questions in the survey that allows us to classify households with financial problems based on self reported information. This dependent variable takes the value 1 if the household has had problems to pay their financial obligations and zero otherwise. As pointed out in Alfaro et al. (2010) the answers to this question do not allow us to distinguish the kind of debt that the household has defaulted, if it has both types of debt. However, we can distinguish the consumption default excluding to household that possess mortgage debts. This allows capturing households with problems in honor their consumption debts.

Our probit model is defined by:

$$\Pr\left(Df=1\right)=\Phi\left(\gamma\ MDSR+\theta\ d\_MDSR+\alpha\ \Pr(u)+X\ \beta\right),$$

where $\Pr\left(Df=1\right)$ represent the probability of giving default, $MDSR$ is our financial risk mea-

[9] They classify dummy variables by percentile of DSR using five groups, 10-30, 30-50, 50-70, 70-90, and larger than 90.

sure, d_MDSR is a dummy variable equal to 1 when the household is above a threshold of 75% of DSR $\Pr(u)$ is the probability of layoff of the household's head, and X represents other demographic variables.

The probability of layoff is given by the observed proportion of workers losing their jobs over the last 3 months in the National Survey of Employment in Chile in the fourth quarter of 2007. The National Survey of Employment in Chile covers 120,000 individuals and therefore allows us to estimate layoff probabilities for highly heterogeneous groups. We considered non-parametric layoff probabilities for all cross-terms for gender, three age groups (below 35, from 36 to 55, above 56), three education groups (primary education, secondary education, and college education), and three economic sectors of activity (primary sector, industry, and services).

The dummy for the high values of DSR is included because there are few households with very high levels of DSR. Since default is a rare event for a household, our model cannot efficiently estimate the effect of DSR on default for a small group of the sample. The household's demographic characteristics include the total income of the household, the number of household's members, the age, the marital status of the household head, sex of the household head and dummies for the educational level of the household head (institution or college).

V. Estimation Results

Table 4 shows the estimation results of our probit model for the determinants of the probability of default. The differences between the first and the second column is that in the later we use 30 data bases with imputation process as recommended by Shafer (1997), meanwhile for the former we use only the original non-imputed data base. In both cases the standard errors were etimated using the bootstrap procedure described before.

The results shows that income has a negative relationship with the probability of default, a result that is common in the literature (La Cava and Simon, 2003; Alfaro et al., 2010), because the income is the main determinant of the re- payment ability of a household. The number of members of the household are positively related with the probability of default. Also, the age and the marital status of the household head are significant. In particular, older head of households have a lower probability to incur in default than younger. For the case of marital status, married men have a lower probability of being in financial distress. Perhaps, this can be explained by the fact that this kind of household could have more than one source of income.

Another highly significant cause of the probability of default is the probability of layoff. It means that the uncertainty respect to the future labour status and income have a great impact in the financial behaviour of a household. Others studies mention the unemployment rate as a determinant of default (May and Tudela, 2005; La Cava and Simon, 2003). However, thos studies use an aggregate measure of unemployment risk, which does not incorporate idiosyncratic aspects of the individuals and hence may not correctly measure the effect of the unemployment on different families.

With regards to the estimated threshold represented by μ in table 4, the value that shows a significant variation in the probability of default is 42.8 (which is equivalent to a 75 for the DSR). Above this threshold the estimated slope is not significant. This means that there is no further increase in the probability of default above this threshold. We believe that a household that reaches these levels of indebtedness is already in financial distress, thus an increase in their debts does not imply in an increase in the probability of default.

Table 4: Probit Results

Variables	(1)	(2)
Log Income	-0.187***	-0.226***
MDSR<μ	0.989**	0.877**
d_MDSR>μ	0.177	0.173
Members	0.145***	0.148***
Age	-0.00887**	-0.009***
Married man	-0.225*	-0.212*
Gender	-0.150	-0.157
Institute	0.189	0.204
College	-0.0207	0.018
Layoffs	13.87***	14.513***
Constant	1.262*	1.750**
Observations	2,317	2,317
Represented Households	2,176,021	2,176,021
Imputations	0	30

Standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1

(1) Estimation includes weights. Standard errors was calculated with bootstrap procedure.

(2) Estimation includes weights and imputations. Standard errors was calculated with bootstrap procedure.

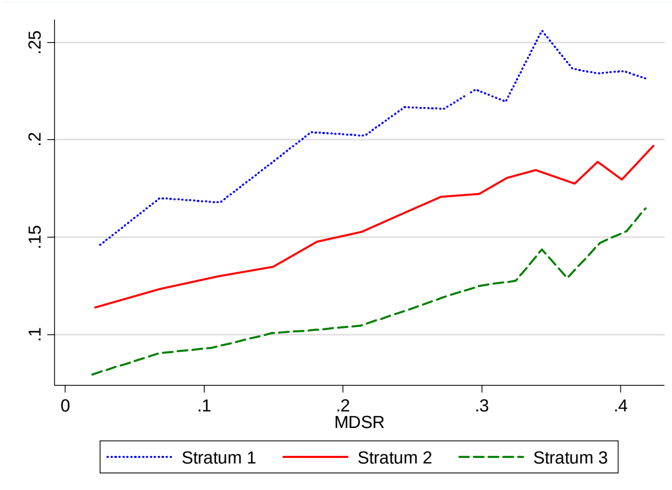
Source: Author's calculation.

VI. A Threshold for Financial Distressed Households

In figure 2 we graph the marginal probability of default for each income strata. The methodology used is similar to the one followed by Dey et al. (2008), but with some important methodological changes. In particular, Dey et al. (2008) use the mean characteristics by groups of MDSR. Given that actually every group possesses different characteristics in several aspects, the comparison is difficult and could be misleading. Unlike Dey et al. (2008), we use the population median for all the other regressora, which allowa us to compare among different MDSR levels. The median characteristics of the population are the following: 47 years old man, married, with 4 members, without university and institute studies, and a probability of layoff of 1.4%.

Conditional on the median characteristics we bracket households by levels of MDSR and income strata. That is, for all the household that belongs to the MDSR level between x% and (x+5) %, we calculate the mean probability of default by income strata. Figure 2 shows that given the level of MDSR, stratum 1 always has a higher probability of default, reaching a probability of default over 20% from a MDSR level of 20%, whereas the strata 2 and 3 are an under 20% for any level of MDSR. Even more, it seems that for higher MDSR levels (nearly 40%) the probability of default of a household that belongs to stratum 3 is almost the same as a household belonging to stratum 1 and with a MDSR of 5% approximately. This fact reflects the high capability of the high income strata to overcome financial problems relative to the lower income strata.

Figure 2: *Marginal Probability of Default by Income Strata.*

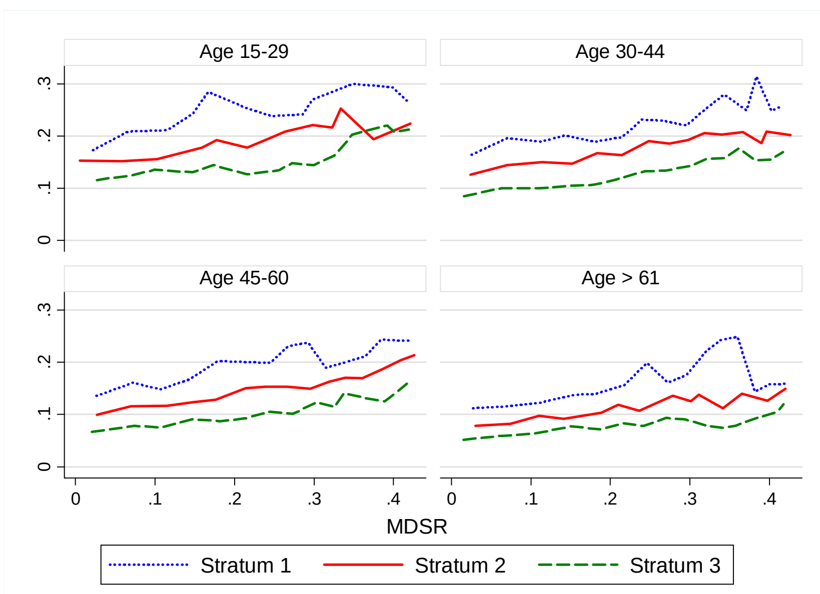


Source: Author's calculation.

Also, figure 2 shows that the probability of default is increasing in the level of MDSR. Also, as raised in Del-Rio and Young (2005), the relationship seems monotonically increasing in strata 1 and 2, whereas for the stratum 3 it seems like a step function represents the relationship between MDSR and probability of default. An important implication of this exercise is that increases in the MDSR level from 20% to 40% (which implies an increase of the DSR from 25% to 41%) increases the probability of default in around 5% in each strata.

Now in a similar exercise, we separate the marginal probability of default by income strata and also by some ranges of age of the household's head. Figure 3 shows that the household in which the head is between 15 and 44 years old show an average 5% more probability of default than those households with head with more than 44 years.

Figure 3: *Marginal Probability of Default by Income Strata and Age Strata.*



Source: Author's calculation.

VII. Debt at Risk (DAR)

Given that we could not find a clear threshold to identify households in financial risk, we try to reflect the degree of exposure of financial institutions to the household sector through the debt-at-risk, proposed by May and Tudela (2005). Table 5 shows the debt-at-risk for the Chilean household sector in 2007 based in information of SHF 2007 for different income and age strata. In the table we see that the debt-at-risk is increasing in the level of income. This means that despite the fact that the higher income households have a lower probability of default, the size of the debt that they possess leads to present the greatest percentage of the debt at risk. Upper income households' debt at risk represents 14% of the consumption debt, which translates into 6% of the total debt. Strata 1 and 2 possess 6% of the debt at risk in consumption and only 3% of the total debt. At an aggregate level, the debt at risk in consumption debt reaches 21.5%, which is equivalent to 9% of the total debt.

On the other hand, the debt at risk shows an inverted U-shape as the age increases and reaches a value of 45 and 60 years. Household heads of this age have 10% of the consumption debt at risk, which implies a 4% of total debt at risk. The range of age with lower debt at risk is that between 15 and 29 years old, likely due to the fact that financial institutions do not grant them large amounts in its credits.

Figure 5: *Debt at Risk.*

	% Indebtedness Household	% DAR in Consumption	% DAR in Total Debt
	64.31	21.53	9.18
Stratum 1	56.57	2.85	1.21
Stratum 2	71.40	4.51	1.92
Stratum 3	73.13	14.17	6.04
Age 15-29	65.55	1.59	0.68
Age 30-44	72.81	7.77	3.31
Age 45-60	68.21	10.02	4.27
Age > 61	47.54	2.15	0.92

Source: Author's calculation.

VIII. Conclusions

We propose a new index to measure household's financial status. This index corrects several problems presented in one of the main indexes used in the literature, the Debt Service to Income Ratio (DSR). Our new index, called the MDSR, allows us to avoid the problems of treatment of outliers and also incorporate households without any transitory income. These are common problems in the literature, which imply that results using the standard DSR are biased, mainly due to their under-measurement of tendency measures such as the mean and standard error.

In order to understand the behaviour of households respect to its default, we estimate a probit model including the MDSR, the probability of layoff of the household's head, and a set of demographic characteristics of the households. Given that we use a survey with an unequal selection probability for different households, we use a bootstrap procedure to calculate the standard errors correctly.

Our results show that the income, age and marital status of the household's head decrease the probability of default, whereas the MDSR and probability of layoffs increase it. Besides, we can not identify a threshold in the MDSR as an indicator of households in financial distress. In fact we show that the relationship between the probability of default and the MDSR is monotonically increasing. The only upper limit found to the MDSR is in a value of 43% (75% of the DSR). Since there are few households with levels of indebtdeness higher than this, it is not possible to estimate increases in financial distress beyond this value. Another important result is that despite the fact that higher income households have a lower probability of default, these households hold more debt than the lower income ones and therefore present the greatest percentage of the debt at risk. This means that the Chilean financial institutions incur more risk from higher-income households.

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