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MEASUREMENT OF HOUSEHOLD FINANCIAL RISK WITH THE SURVEY OF HOUSEHOLD FINANCES*

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Abstract

In this paper we study the determinants of financial risk of households. We estimate the probability of default of household using a probit model with two novel variables: (i) a Modified version of the Debt Service Ratio index (MDSR) and (ii) the probability of job layoff of the head of the household. Our new index allows us to include households without any transitory income in the analysis and solve the outliers' problem underlying the standard Debt Service Ratio (DSR). The probability of layoff allows us to incorporate the uncertainty with respect to the labor status and income of the household's head. In addition, we study the marginal probability of default for different income strata and age strata by levels of MDSR, conditional in others characteristics. We use micro-data from the Survey of Household Finances (SHF) of the Central Bank of Chile. Our estimates show that both, the MDSR and the probability of job layoff, are positively related with the probability of default. In fact, we found a monotonically increasing relationship between the probability of default and the MDSR. Our results allow us to assess the probability of default of the debt outstanding, and to project it under different scenarios.

Resumen

En este artículo estudiamos los determinantes del riesgo financiero en los hogares. Estimamos la probabilidad de no pago de los hogares utilizando un modelo probit con dos variables nuevas: (i) una versión modificada de la razón de carga financiera sobre ingreso (RCIM) y (ii) la probabilidad de desempleo del jefe de hogar. Nuestro nuevo índice nos permite incluir en el análisis a hogares sin ingreso transitorio y además resolver los problemas de *outliers* subyacentes en la medida tradicional de carga financiera sobre ingreso (RCI). Por su parte, la probabilidad de desempleo nos permite incorporar la incertidumbre respecto al estado laboral y el ingreso del jefe de hogar. Además, estudiamos la probabilidad marginal de no pago para diferentes estratos de ingreso y edad para distintos niveles del RCIM, condicional en otras características. Utilizamos datos micro de la Encuesta Financiera de Hogares (EFH) del Banco Central de Chile. Nuestras estimaciones muestran que tanto el RCIM como la probabilidad de desempleo están positivamente relacionados con la probabilidad de no pago. De hecho, encontramos una relación monotónica creciente entre la probabilidad de no pago y el RCIM. Nuestros resultados nos permiten evaluar la probabilidad de no pago de la deuda mantenida, y proyectar esta bajo diferentes escenarios.

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1 Introduction

Household debt and indebtedness[1] has been increasing in several economies during the last two decades. For developed economies such as the US and the UK, household debt represents more than 100% of GDP (Debelle, 2004; Girouard et al., 2006; Karasulu, 2008; Ma et al., 2009). The growth of indebtedness in the household sector is attributed to financial innovation and decreases in nominal and real interest rates (Debelle, 2004). In Chile, the average growth rate of households' debt was 12.8% in real terms during the period 2000-09, while disposable income did so by 5.5% only. Indebtedness, measured as total household debt over disposable income, was over 60% since 2007 (Central Bank of Chile, 2010).

A high level of household indebtedness affects the economy through two channels: financial stability and monetary policy (Debelle, 2004; Benito et al., 2007). With regards to the first channel, as long as households' debt represents a large item in banks' balance sheets, high levels of household indebtedness imply a high level of risk for those assets.[2] This increases the fragility of the financial system.

Second, but not less important, are the effects of indebtedness on monetary policy. High levels of household indebtedness could make households less responsive to changes in the interest rate. This is because high level of indebtedness could constrain households' access to credit, reducing the power of monetary policy. In addition, higher indebtedness imposes pressure on monetary policy, since an increase in the interest rate generates a rise in the debt burden if debt has a floating rate or its term is short and has to be renegotiated. This exposes the household to a higher default probability and to a reduction on its disposable income.

Traditionally, the impact of households' indebtedness in the financial sector is assessed using aggregate data. Although aggregate data gives us a useful first approximation, it hides us how debt is distributed among households, which is key to determine the financial risk of a given amount of debt (Dey et al., 2008; Herrala and Kauko, 2007; Faruqui, 2008). With this in mind, several countries have developed surveys at the household level with the purpose of analyzing risk in the household sector.

The purpose of this article is to estimate the risk of household debt using information of debt at the level of households. For this, we search for the main determinants of default of households' consumption debt. In the estimation we incorporate two novel variables: (i) a new financial indicator, the Modified Debt Service Ratio (MDSR) and (ii) the probability of layoff of household's head. On the one hand, the MDSR allows us to eliminate the outliers' problem in the traditional DSR and to include households even if their (transitory) income is zero, whereas the probability of layoff 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'

[1] Indebtedness is the relation between the stock of debt owed by a household and a measure of its resources, which could be income or assets.

[2] Ma et al.(2009), using 2007 data, note that the share of loans to household in total bank loans varies significantly across country, from 15% in China to 70% in Australia. In Chile that share reaches a 33.4%.

head. Finally, we calculate the debt at risk in the Chilean households using the procedure proposed by May and Tudela (2005).

To analyze the probability of default at the household level, we use the Survey of Household Finances (SHF) 2007, of the Central Bank of Chile, which collects information of 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. Section 2 makes a review of the related literature and introduces the standard Debt Service Ratio (DSR). Section 3 describes our new financial index: the Modified Debt Service Ratio (MDSR). Section 4 describes the estimation model of the probability of default. Section 5 shows the results of the estimations. Section 6 presents the relationship between the MDSR and the probability of default. Section 7 calculates the estimated debt at risk. Finally, section 8 concludes.

2 Related Literature

In recent years, the empirical literature studying the determinants of households' default has increased due, mainly, to the increased availability of suitable microdata. A large part of the literature finds the Debt Service to Income Ratio (DSR) to be significant in explaining default. Some papers focus on determining whether there are relevant threshold values for DSR, above which the probability of default increases substantially. This, to validate a practice observed in some countries where credit providers operate with some thresholds like those in mind.[3] It should be noted, however, that the existence or not of such thresholds is not critical for the validity of the practice. Maximum levels of DSR may guide lenders behaviour not only because they think risk accelerates above it, but simply because it has reached their level of tolerance to risk.

In a seminal paper, Fay et al. (2002) use the Panel Study of Income Dynamics to estimate a model of household bankruptcy for the US. Their results show that *household income* is negatively related to the probability of filing for bankruptcy. Among demographic variables, the *age of the household head*, the head's *education level*, and *family size* are all statistically significant with the expected signs. On the other hand, *adverse events* (divorce, unemployment, health problems of the household head or spouse) do not affect the decision of filing for bankruptcy.

Böheim and Taylor (2000) use the British Household Panel Survey (BHPS) to analyze what factors influence households experiencing problems to pay the rent or mortgage in the previous year. Their findings show that *household financial history* and *financial surprises* are the main determinants of financial difficulties.[4] Also, *age of household head*, *regional unemployment* rate

[3] Greninger et al. (1996), based on the opinion of 156 experts, indicates that a DSR level under 35 % is reasonable, but a households with a DSR higher than 45 are over a danger point. Faruqui (2008), reports that the industry standard is 23% for such a number in Canada. Karasulu (2008) reports that this level is 40% in Korea.

[4] To create a financial surprises indicator, the household must answer whether they expect to be better off, same, worse off, comparing the current year. The authors compare this answer to that of a question posed in the following year which compares its current situation with that of the previous year.

and *unemployment of the household head* are important variables. In a similar study, May and Tudela (2005) analyze the determinants and dynamics of mortgage defaults using the BHPS. They define financially distressed households as those who experienced problems to serve their debts in the previous year. They also find that current financial distress is positively correlated with past *history of financial problems*. Also, *becoming unemployed* and having *high loan-to-value ratios* (ratio of the original mortgage to the original value of the house) increase the probability of default. They found that mortgage (interest only) DSR above of 20% is positively related with the probability of payments problems. Among macroeconomics variables, only the *interest rate* was significant, but *unemployment* and *housing prices* were not. Bowie-Cairns and Pryce (2005) found similar trends in mortgage repayment difficulties analyzing the same data. They state that the ability to service debts by a household increases with *education level*, *age* and the *household head being married*.

DeVaney (1994) assesses the effectiveness of financial ratios as a predictor of household insolvency.[5] As argued in DeVaney and Lytton (1995) "*the primary function of ratios should be to act as indicators or red flags - to point to areas of acceptable or unacceptable results or conditions*". Using the Survey of Consumer Finances of the US for 1983 and 1986, she finds that the DSR is useful as a predictor of household insolvency. Her results show that households with a DSR higher than 35 % should be considered to have a high probability of insolvency.

Del-Rio and Young (2008) use the BHPS to identify the level at which unsecured debt becomes a problem for the typical household and what factors affect this outcome. They use self-reported information that indicates the extent to which the payment of debts is a financial burden on a household.[6] They found that the main determinant of debt problems is the unsecured DSR.[7] In particular, they find evidence that reporting difficulties with debt is monotonically increasing in the unsecured DSR. Therefore, no specific threshold was identified. Also, they found that the level of mortgage payments to household income (above 20%, as May and Tudela, 2005), *households' financial wealth*, the *health of household head*, *ethnicity*, *marital status* and being *unemployed* are other factors that cause debt problems.

Holló and Papp (2007) use the Household Survey of Central Bank of Hungary to determine the main idiosyncratic driving forces of credit risk. They estimate a logit and a neural network model of household credit risk, where financially distressed households are defined as those with more than one month payment arrears in the previous twelve months. Their results suggest that individual factors as *disposable income*, the *number of dependants* and particularly the *employment status of the household head* and the DSR, are significant determinants of household default probability.

[5] 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.

[6] If the household answered the question, they have three alternatives: Heavy burden, somewhat of a burden or not a problem.

[7] The DSR is represented by 5 dummies for percentiles 10 to 30, 30 to 50, 50 to 70, 70 to 90 and more than 90. They use dummy variables not to impose a particular functional relationship between the level of the debt to income ratio and the probability of reporting debt problems.

Faruqui (2008) analyze the distribution of the DSR in Canada and compare the results with the US. In his analysis Faruqui excludes households with zero debt and households with a DSR above 50%, which is an arbitrary cut-off.

Dey et al. (2008) present a framework to simulate how the DSR reacts to changes in indebtedness and interest rates. The authors estimate a model of mortgage-debt deliquency to identify a threshold for the DSR. They found that beyond a DSR of 35 there is a significant increase in the probability of mortgage-debt deliquency.[8] The authors exclude households with a DSR equal to or above 50% due to the possibility of reporting errors. To apply their model, they use two different sources of data, the Ipsos Reid Canadian Financial Monitor and the Statistics Canada's Survey of Financial Security. They find a negative relationship between income and their measure of vulnerability. Also, the educational level is important, where households with lower education have the greatest vulnerability.

Using the European Community Household Panel Survey, Georgarakos et al. (2010) study households' attitude towards mortgage indebtedness in twelve European countries. They define financially distressed households as those households who declare that their *housing costs* are a financial burden for them.[9] In their estimations, they allow for non-linear influence of after tax income and the mortgage DSR.[10] They find that a higher DSR is a main determinant of financial distress, however, the predicted probabilities of reported financial distress as a function of mortgage DSR are quite different across countries both in level and slope. They use a 30% of the DSR as a threshold to classify individuals as a risky borrowers and exclude households with a DSR in excess of 3. Also, *education*, *health problems*, *labour status*, *income level* and *unemployment*, are relevant determinants of financial distress.

Alfaro et al. (2010) study household debt default behavior using the SHF of the Central Bank of Chile. They distinguish between mortgage and unsecured (consumer) debt default. They find that only *income* is significantly related to both types of default, the *education level* is important for mortgages default, and DSR, *age* and the *number income earners in the household* are relevant for default of unsecured debt.

2.1 Debt Service Ratio Analysis

One of the most used indexes to describe household financial risk and its evolution over time across countries is the Debt Service to Income Ratio (DSR). It shows the percentage of households' income that is destined to pay for financial obligations. That is, a household with a high DSR means that this household must spend a large fraction of its income to serve its debts. This index can be built using data at the aggregated level from national accounts or using microdata at the household level from surveys. However, aggregate data could hide crucial facts about the

[8] The last reports of the Financial Stability Review of the Bank of Canada use as a DSR vulnerability threshold, 35 and 40. Previously, the thresholds were 23 and 40 (see for instance, Bank of Canada, 2007).

[9] As in Del-Rio and Young (2005), households have the same three possible answers.

[10] They use a logarithmic transformation for tax income and a second order polynomial form for the mortgage DSR.

distribution of the debts and, therefore, the real magnitude of the debt at risk. Hence, working with micro data presents great benefits for policy makers.[11]

Specifically, the functional form of the DSR is represented by:

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

where db_h is the debt burden (defined as the required payment of interest and principal in the period) and y_h, the income of the household h in the same period. In particular, 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 consumption 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 $p_{j,k}$.

One of the main characteristics of the DSR is the simplicity in its construction. However, this indicator is not exempt of problems. We focus on two important problems of DSR: (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 related to the non-linearity in the relation of DSR with income. In particular, if income falls, DSR increases at an accelerating rate. This creates an outlier problem. The standard solutions to avoid this problem are to truncate the DSR or to censor it. However, these solutions bias central tendency measures and non-central measures in the distribution of the DSR. On the one hand, if we truncate the DSR, we exclude from the sample households with either high debt service or with low income, and hence, we would be leaving out of the analysis those households with high financial risk. On the other hand, when we censor the DSR, we are reducing the financial risk measure in an artificial way, since this procedure accumulates households in a specific point of the distribution.

The second problem is related with households without any income. In this case, the standard solutions to remove those households from the sample or to include them with the maximum DSR of the sample. In the first case, if we exclude those households from the analysis, we will not be considering those households with the greatest financial risk. In the second case, if we include them with the maximum DSR into the sample we may be generating an upward bias in the distributional statistics.

In order to stress our points, we present in Table 1 a set of statistics for three alternative ways of dealing with the problem of DSR used in the literature, when applied to households in the EFH 2007. The first line shows statistics of the standard DSR excluding households with no income,

[11] See ECB (2009).

the second line presents the DSR censored in 100%[12], the third line shows the DSR truncated in the median (as in Faruqui, 2008) and, the fourth line shows the standard DSR, but including households without any income, where these households receive the maximum DSR level in the sample.

Table 1: Characterization of alternative DSR's distribution.

	% Indebted households	Mean	Standard Deviation	Median	Interquartile Range	P 99
Standard DSR	54.77	35.29	87.92	19.79	30.63	187.92
Censored DSR	54.97	28.59	26.00	19.83	30.73	100.00
Truncated DSR	46.28	19.12	13.08	16.00	20.18	48.93
DSR with households without income	54.97	41.77	139.99	19.83	30.73	240.00

Censored DSR: Standard DSR censored in 100; Truncated DSR= Standard DSR truncated in 50. DSR with households without income receive the maximum DSR of the sample. Statistics include only households with a positive debt burden. Source: Authors' calculations.

Table 1 shows that the alternatives to present the DSR generate a great dispersion into several statistics. In particular, the first row shows that the standard DSR is potencially subject to two problems: the exclusion of household without income and the presence of outliers. In this case, the first problem is bounded, because the standard DSR excludes only 0.2% of the total households with debt.[13] The second problem is more relevant in our case. In fact in the 99 percentile, the DSR reaches a 188%, which is a high value with respect to the median and the mean. The second row presents the DSR censored at 100%. This alternative reduces the variance of the index, especially in the right tail of the distribution where all the financially distressed households belong. However, censored DSR removes the heterogeneity among households with high DSR . The third row shows the strong effects that truncating the DSR on the median (as some authors suggest) produces on the statistics. In fact, this alternative excludes around 8.7% of the household with debt, which are also those households with greater financial risk in the sample. Finally, in the fourth row we show the effect when households without income receive the maximum DSR of the sample. While this solve the problem of households' exclusion, it is clear that this impairs the distributional characteristics of the index, increasing its mean and also its standard deviation.

These results imply that the rule used to construct the DSR may lead us to different conclusions with respect to the financial health of Chilean households. For this reason, in the next section we introduce a change in the DSR to generate a metric of indebtedness which is less sensitive to extreme observations.

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

[13] Even though this is a small amount, it represents a 1.4% of the households that belong to the first five income deciles which are the most financial distressed households.

3 New financial risk index: MDSR

In this section we introduce a new index to measure the financial status of a household. This index, called the Modified Debt Service Ratio (MDSR), is basically a transformed version of the standard DSR, which allows us to eliminate the problems of the standard DSR showed in the previous section. The MDSR is described as follows:

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

where db_h and y_h are defined identically as the ones in the DSR. It should be noted that the interpretation of the MDSR is not as direct as in the standard DSR, that is, the MDSR does not represent the proportion of the household's income destined to serve its debts. However, there is a clear relationship between these two indexes that helps to interpret the results.

In particular, the MDSR can be expressed in terms of DSR. In fact, the MDSR has a one to one mapping with the DSR, which is given by:

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

The main difference between these indexes is that MDSR is bounded. Figure 1 clearly shows that the MDSR is not affected by extreme observations, while the DSR converges to infinity as household's income goes to zero. This fact allows us to include households with low or even zero transitory income, without the need to impose an arbitrary upper value for the DSR (as in the truncated or censored version of the DSR). Indeed, these households will always have a MDSR below or equal to one. This crucial difference allow us not to discard from the analysis households with more financial problems and, therefore, with higher probability of default, as most of the previous literature.

Figure 1: Income vs DSR and MDSR.

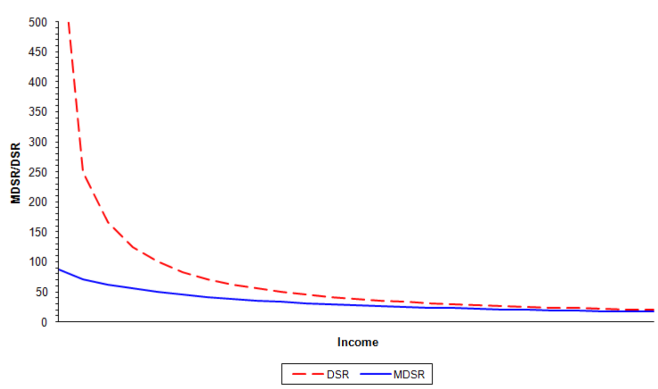


Table 2 presents the equivalence between the two metrics. In particular, it shows the MDSR range equivalent to each of the first 10 deciles in DSR. In addition, the table shows the fraction of indebted households and the fraction of debt accumulated in each decil. We see that more than 25% of the households with debt are concentrated in a MDSR lower that 9.1% (10% in the DSR terms). This proportion of households has a relatively low participation in the total amount of the debt representing only an 10%. In fact, more than 50% of the debt is concentrated in households with an MDSR level between 9.2% and 28.6% (DSR between 10% and 40%). If we focus on the last line of the table 2, households with income lower than the debt burden correspond to 4.8%. These households are those that cause the problems in the tail of DSR. As discussed, in some papers these households are dropped, despite the fact that they are the most distressed households. These households maintain around 8% of the total debt and represent the 23% of the consumption debt, significant amounts in both cases. In fact, these households maintain the largest proportion of consumption debt in comparison with any other of the first ten deciles of DSR.

Table 2 : Distribution of the Debts expressed in DSR and MDSR.

DSR	MDSR	% Indebted Households	Total Debt	Consumption Debt	Mortgage Debt
0 - 10	0 - 9.1	26.27	10.57	7.22	10.35
11 - 20	9.2 - 16.7	24.07	21.19	14.24	24.39
21 - 30	16.8 - 23.1	14.40	16.88	12.64	20.35
31 - 40	23.2 - 28.6	10.01	13.13	11.38	13.04
41 - 50	28.7 - 33.3	9.43	10.91	11.13	9.82
51 - 60	33.4 - 37.5	3.84	5.07	5.37	5.40
61 - 70	37.6 - 41.2	2.41	4.90	5.91	4.52
71 - 80	41.3 - 44.4	1.63	2.60	1.86	2.31
81 - 90	44.5 - 47.4	1.49	4.14	3.79	3.52
91 - 100	47.5 - 50	1.61	2.69	3.05	2.61
More than 100	More than 50	4.83	8.01	23.37	3.38
Total		100	100	100	100

Source: Authors' calculations. The DSR includes households without transitory income.

In table 3, we compare the performance of the MDSR against the alternatives to fix problems with DSR discussed previously. In particular, we concentrate our analysis on the behavior of indicators of the right tail of their distribution. We explore the behavior in three zones: (i) the 75th and 90th percentile; (ii) the 90th percentile and over, and (iii) above the 95th percentile. For each zone, we show the percentage of indebted households, the difference between the maximum and the minimum of each group and their standard deviation.

If we focus on the first group (households between p75 and p90), we can see that the percentage of indebted households are the same among strata for all measures except the **truncated DSR**. This is because this strategy excludes all households with a DSR over the median (Faruqui, 2008). However, independent of the point of truncation, the number of households always would be lower than that of the other measures. Therefore, if we use this measure we will always been eliminating relevant information of our sample.

Focusing on the second group (households over p90), we see that the **standard DSR** including households without income greately increases its variance. This is not suprise since these households receive the highest DSR in the sample. However, this procedure give us an excess of variance to the data. In fact, the standard deviation is greater than 80% in all strata, and also, the difference of the maximum and the minimum across strata is extremely high, showing a high dispersion of the DSR.

Finally, if we focus on the third group (households over p95), we see that the **censored DSR** has no variability (its standard deviation is zero among strata) since it concentrates all households in a specific point of the distribution. Therefore, this index give us little information of this group, which is one which we would like to distinguish the most.

As this analysis shows, none of these strategies provide a good alternative to analyze financially distressed households. However, the MDSR is exempt of the problems mentioned, since every statistic calculated for the MDSR is well behaved across groups and, also, it includes in the sample all households with debts even though they do not have any income. These facts allow us to measure in a better way households in financial risk.

Table 3: Comparison between Indicators.

	Households between p75 and p90			Households over p90			Households over p95		
Indicator	% indebted household	|p90-p75|	Standard Deviation	% indebted household	|max-p90|	Standard Deviation	% indebted household	|max-p95|	Standard Deviation
MDSR									
Total Households	14.51	12.50	3.39	9.87	58.90	14.28	4.92	50.00	13.89
stratum 1	16.12	12.50	3.63	13.89	58.88	15.47	7.85	50.00	15.09
stratum 2	13.78	12.05	2.93	7.64	47.97	12.92	3.06	37.13	11.90
stratum 3	12.80	12.45	3.47	6.28	50.08	10.10	2.66	40.78	9.09
Censored DSR									
Total Households	14.51	29.72	7.93	9.87	30.23	10.66	4.92	0.00	0.00
stratum 1	16.12	29.72	8.49	13.89	30.15	9.72	7.85	0.00	0.00
stratum 2	13.78	28.74	6.81	7.64	30.00	11.85	3.06	0.00	0.00
stratum 3	12.80	29.58	8.15	6.28	30.23	10.77	2.66	0.00	0.00
Truncated DSR									
Total Households	12.61	11.85	3.53	8.36	9.72	2.75	4.20	5.78	1.59
stratum 1	12.87	11.85	3.84	9.06	9.72	2.76	3.48	5.12	1.36
stratum 2	12.59	11.64	3.30	8.82	9.24	2.50	5.39	5.78	1.61
stratum 3	12.19	11.76	3.22	6.44	9.71	2.96	3.64	5.74	1.85
Standard DSR*									
Total Households	14.51	29.72	7.93	9.87	1806.15	398.62	4.92	1775.92	527.32
stratum 1	16.12	29.72	8.49	13.89	1806.07	502.19	7.85	1775.92	625.64
stratum 2	13.78	29.74	6.81	7.64	751.60	169.46	3.06	713.17	226.89
stratum 3	12.80	29.58	8.15	6.28	963.57	84.37	2.66	931.73	105.61

Censored DSR= DSR censored in 100; Truncated DSR= DSR truncated in 50; Standard DSR*= DSR including households without income. These households receive the maximum DSR in the sample. Stratum 1 represents households that belong to the first to fifth income deciles; Stratum 2 represents households that belong to the sixth to eighth income deciles; Stratum 3 represents households that belong to the ninth to tenth income deciles. Statistics include only households with a positive debt burden.

Source: Authors' calculation

4 Probability of Default

We focus our analysis on unsecured (consumption) debt to define default, for several reasons. First, the percentage of household with unsecured debt reaches a 62% in the Chilean households, whereas the fraction of households with mortgage debt reach only a 13%. Second, consumption debt is riskier than mortgage debt, because mortgage debt is collateralized and financial institutions do not lend the entire value of the house being purchased. Moreover, mortgage loans are primarily concentrated in the percentiles of the population with higher income, and, a priori, with less financial problems. In fact, only an 6% of the first income stratum possesses mortgage debt, while this percentage reaches 16% for stratum 2 and 30% for stratum 3 (Central Bank of Chile, 2010).[14] On the other hand, a considerable part of all income strata have consumption debt (55%, 69% and 67% for strata 1, 2, 3, respectively).

To construct the dependent variable, we use data from the Survey Households Finances (SHF) 2007, conducted by Central Bank of Chile. In particular, we use some questions in the survey that allow us to classify households with financial problems based on self reported information.[15] The first question is the following:

In the last twelve months, has occured some event in your household that did not let you pay your debts? The head of the households have four possible answers: (i) yes, (ii) no, (iii) do not answer or (iv) do not know. The answers to this question do not allow us to distinguish the kind of debt that the household has had problems with, if it has both types of debt. However, we can distinguish the default of unsecured debt by excluding households with default on mortgage debts. We do this with the following question:

Currently, are you paying your mortgage credit? The head of the households have six possible answers: (i) yes, I am paying my debts in time (ii) yes, I am paying my debts with delay (iii) no, I am not paying, despite of having outstanding debts, (iv) no, I am not paying, I finished my payments, (v) do not know, or (vi) do not answer. If the head of the household answered (ii) or (iii) we exclude these households from the sample, since these are the cases where the household is in default of its mortgage debt.

Hence, the dependent variable takes the value 1 if the household has had problems to pay their financial obligations during the last twelve months and zero otherwise.

4.1 Probability of Layoff

As it is noted in other papers, the level of unemployment is one of the biggest causes of the financial default (see for instance Boheim and Taylor, 2000 or May and Tudela, 2005). However, those 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.[16] On the other hand, other articles have identified the currrent labour status

[14] Stratum 1 represents households that belong to the first to fifth income deciles; Stratum 2 represents households that belong to the sixth to eighth income deciles; Stratum 3 represents households belonging to the ninth to tenth income deciles.

[15] For further details see *Cuestionario EFH 2007* in http://www.bcentral.cl/estadisticas-economicas/financiera-hogares/index.htm

[16] Moreover, using the level of unemployment do not have any sense in a cross sectional framework.

of the household's head as a signiticant variable in the probability of default (see for instance Del-Rio and Young, 2005 or Holló and Papp, 2007). However, since the SHF (2007) asks for defaults occurred in the last twelve months, the current labour status is not useful to evaluate the probability of default. Moreover, Jones and Naudon (2009) show that the probability that an unemployed find a job within the next three months is around 55% in Chile. This implies that the relationship between the current employment status of a household head and his status during the previous year is weak, since most workers that were unemployed over some period of the last 12 months are already employed and most of the currently unemployed were actually employed over the previous year. In this sense, we estimate the probability of layoff of some groups in order to incorporate in the model a stochastic measure of income uncertainty and labour stability, which reflects more adequately the workers' probable labor experience over the previous 12 months.

To build the probability of layoff, we use information about previous labour experience, industrial sector and geographic location of current and previous jobs contained in the Supplementary Survey on Income (SSI).[17] Then, using the personal and labour characteristics of the household head, we match the probability of layoff from SSI to the SHF. The SSI survey 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 geographical zone (metropolitan area and other area) and three economic sectors of activity (primary sector, industry, and services).

Specifically, the probability of layoff (δ) is defined as:

$$\delta \equiv \Pr\left(U_{i,t} = 1 \,/\, E_{i,t-1} = 1, X_i\right), \tag{1}$$

where $U_{i,t} = 1$ represents that the head of the household i is unemployed at date t, $E_{i,t-1} = 1$ the head of the household i was employed at date $t-1$ and X_i are the characteristics of the household's head. Using the individual workers characteristics we can estimate the quarterly probability of layoff by the proportion of workers that lost their jobs in the last 3 months, that is, the fraction of workers with an ongoing unemployment spell (dur_j) of less than 12 weeks (Shimer, 2007, 2008):

$$\delta\left(X_i\right) = \frac{\sum_j 1\left(X_j = X_i, dur_j \leq 12\right)}{\sum_j 1\left(X_j = X_i\right)}. \tag{2}$$

Based in 2 and using the National Employment Survey we calculate the probability of layoff by head household conditional in idiosyncratic characteristics.[18] Table 4 shows the estimated probabilities of layoff by geographic location and industrial sector.

[17] The SSI, implemented by the Chilean National Statistical Institute, collects information about income and labour status of the household's head.

[18] The probability of layoff is given by the observed proportion of workers losing their jobs over the last 3 months in the National Employment Survey in Chile in the fourth quarter of 2007.

Table 4: Probabilities of Layoff (%).

	Metropolitan area	Other area
Primary	1.69	5.84
Manufacture	2.01	4.31
Service	2.02	1.68

Note: Primary sector includes fishing, agriculture, mining and forestry.

4.2 Determinants of the Probability of Default

In this section, we study the main determinants of the probability of default. Several articles study this relationship using the DSR as an index of financial distress However, these articles do not take into account the problems presented by it, which, as we show, may have significant effects on the results. To overcome this problems, we use the MDSR to test whether this index is a relevant determinant of the probability of default of a household. Also, we include another novel variable to the model, the probability of layoff, which allows us to include a measure of income uncertainty and labour stability.

We search the existence of a threshold for the MDSR where above it households increase substantially its probability of default. To do this, we include two dummies to allow us to test changes in the relationship between the MDSR and the probability of default. In this sense, these dummies allow us to have three different slopes using interactive variables (see Annex A). We perfom a series of estimations changing these dummies, checking whether the parameters estimated are significant or not. This procedure allows us to detect statistically significant changes in the estimated parameters. Del-Río and Young (2005) used a similar procedure for British households, where they constructed several dummy variables for different levels of DSR.[19] However, unlike us, they use discrete variables rather than continuous ones in order not to impose a particular functional form between the DSR and the probability of reporting debt problems. They do not find 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 problem can be solved using imputation method (Shafer, 1997), which is the standard solution in the literature. However, considering population weights and multiple imputations in the estimation process is a hard task, because there is no analytical solution to estimate 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

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

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 3,000 bootstrap replicas for the estimation.

We define our probit model by:

$$\Pr\left(Df=1\right)=\Phi\left(\gamma\ MDSR|_0^q+\theta\ MDSR|_q^{\mu}+\pi\ MDSR|_{\mu}^1+\alpha\Pr(u)+X\beta\right), \tag{3}$$

where $\Pr\left(Df=1\right)$ represent the probability of giving default, $MDSR$ is our financial risk measure, where q and μ specify MDSR thresholds and γ, θ and π are the parameters associated to different slopes (Annex A explains the way the estimation of thresholds is implemented). $\Pr(u)$ is the probability of layoff of the household's head, and X represents other demographic variables. Household's demographic characteristics include the total income of the household, the number of household's members, age, marital status of the household head, gender of the household head and dummies for the educational level of the household head (university or other tertiary education).

Table 5 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 former we use only the original non-imputed data base while in the latter we use 30 data bases with imputation as recommended by Shafer (1997). In both cases the standard errors were estimated using the bootstrap procedure described before.

Table 5: Probit Results.

Variables	(1)	(2)
Log Income	-0.137*	-0.216***
Members	0.135***	0.153***
Age	-0.0079**	-0.01***
Married	-0.135	-0.129
Gender	-0.251**	-0.235**
University education	-0.0728	-0.026
Other tertiary education	0.174	0.203
Prob. of Layoff	6.795*	8.116**
MDSR$<\mu$=42.8	1.173**	0.878*
MDSR$>\mu$=42.8	0.233	0.312
Constant	0.724	1.812*
Observations	2,009	2,009
Represented Households	1,925,144	1,925,144
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: Authors' calculation.

The results show that income has a negative relationship with the probability of default, a result that is common in the literature (Böheim and Taylor, 2000; Fay et al., 2002; Holló and Papp, 2007; Alfaro et al., 2010; Georgarakos et al., 2010). The number of members of the household is positively related with the probability of default, a results previously find by Fay et al. (2002) and Holló and Papp (2007). While the age and the marital status of the household head reduce the probability of default, only the former is significant. In particular, older head of households have a lower probability to incur in default than younger ones.[20] Also, the gender of the household's head is significant. In this sense, man have a lower probability of being in financial distress. These findings are in line with the ones in Bowie-Cairns and Pryce (2005) and Alfaro et al. (2010). Regarding educational level, none of the variables were significant. Alfaro et al. (2010) obtain similar results using unsecured debt. However, their estimations using secured debts suggest that education is an important variable to explain mortgage payment difficulties. Indeed, they stress that some demographic or personal variables are specific to a particular type of debt.

Another significant cause of default is the probability of layoff. It means that the uncertainty respect to the labour status and income have a great impact in the financial behavior of a household. Böheim and Taylor (2000) and May and Tudela (2005) find a related result, but using the unemployment rate as a determinant of default. However, these aggregate measure of unemployment affects in a similar manner to all households without taking into account different idiosyncratic aspects of the individuals. Del-Rio and Young (2005) use the current labour status of the household's head. They find significant effects of being unemployed and being self-employed. The former increases significantly the probability of payments deliquency, meanwhile the latter find debt to be less of a problem.[21] However, unlike us, their dependent variable is constructed using a contemporary question. Also, Holló and Papp (2007) use the job status of the head of the household to proxy whether the household is (as they called) in the "*low income*" state. They found that unemployment increases the likelihood of having financial problems since it is the main source of unexpected changes in income. However, their dependant variable is based on payment problems occurred in the previous twelve months and, therefore, using our variable is more suitable.

Regarding MDSR thresholds, we find, after several estimations (see Annex A), that only one threshold (μ) was stadistically significant. Our final specification showed in table 5 contains the estimated threshold represented by μ. The value that shows a significant variation in the probability of default is an MDSR of 42.8 (which is equivalent to a 75 for the DSR), this implies a positive slope of the MDSR between 0 and 42.8. Above this threshold, the estimated slope is not significant. This means that there is no further increase in the probability of default. We believe that a household that reaches these levels of indebtedness is already in financial distress, thus an increase in its debts does not add a significant increase in its probability of default. However, below that threshold, the probability of default increases monotonically and significantly with the MDSR. Indeed, our results show a monotonically increasing relationship between the probability of default and the MDSR.

[20] Böheim and Taylor (2000) suggest that the risk of housing finance problems is quadratic in age. In fact, the risk is increasing till the age of 40 and declining thereafter. Fay et al. (2002) and Alfaro et al. (2010) found a similar result.

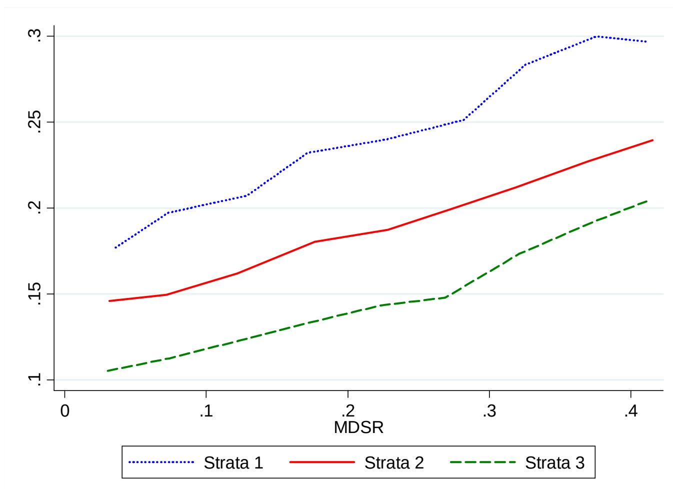
[21] Georgarakos et al. (2010) find similar results for unemployed and self-employed.

4.3 The relation between MDSR and the probability of default

In this section, we study the relation between MDSR and the probability of default for different characteristics of households. Particularly, we focus our attention on different income strata and on the age of the household head. In figure 2 we graph the marginal probability of default for each income strata conditional on other characteristics. The approach used is similar to the one followed by Dey et al. (2008) with some important methodological changes. In particular, Dey et al. (2008) use the mean characteristics by groups of DSR. 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 regressors, which allows us to compare and interpret the results 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 1.67%.

Conditional on the median characteristics we group 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 25% for a MDSR level of 30%, whereas the strata 2 and 3 are under 25% 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 10% approximately.

Figure 2: Marginal Probability of Default by Income Strata.

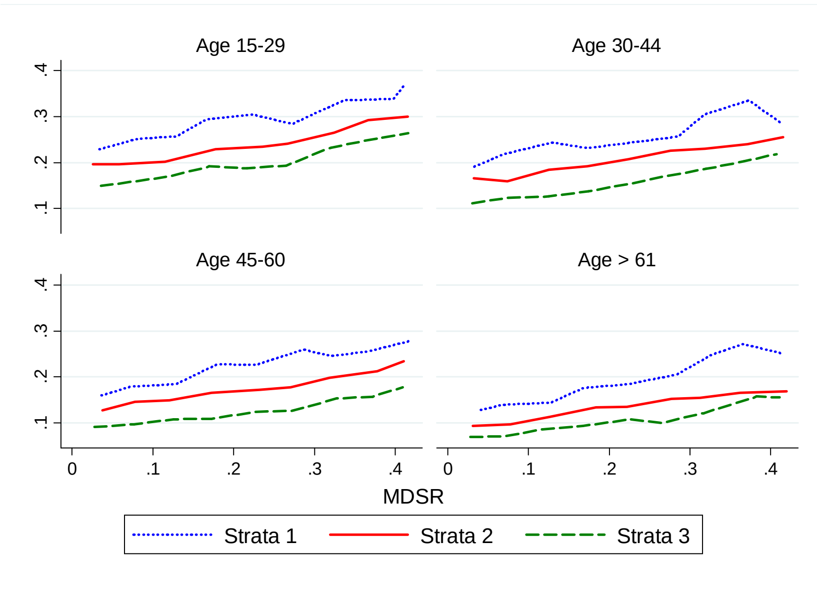


Note: Equivalence between MDSR and DSR: 0.1MDSR=0.11DSR, 0.2MDSR=0.25DSR, 0.3MDSR=0.43DSR, 0.4MDSR=0.66DSR.

Also, as we state above, figure 2 shows that the probability of default is increasing in the level of MDSR. Also, as raised in Del-Rio and Young (2008), the relationship seems monotonically increasing in strata 2 and 3, whereas for the stratum 1 it seems more like a step function. An important implication of this exercise is that, an increase in the MDSR level from 20% to 40% (or from 25% to 66.7% in DSR) increases the probability of default in more than 5% in each strata.

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 households in which the head is between 15 and 44 years old show, on average, a 5% more probability of default than those households with a head with more than 44 years. Moreover, it is quite clear that younger households' head are riskier than other households, controling by income. Moreover, even richer younger households are riskier than other households with less income but with an older household head for a particular MDSR level.

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



Note: Equivalence between MDSR and DSR: 0.1MDSR=0.11DSR, 0.2MDSR=0.25DSR 0.3MDSR=0.43DSR, 0.4MDSR=0.66DSR.

5 Debt at risk (DAR)

In this section, we calculate the degree of exposure of financial institutions to the household sector through the debt at risk (see May and Tudela, 2005). This systemic risk indicator is the sum across households of their consumption debt multiplied by the estimated probability of having payment problems of each household using the probit model of the previous section.[22]

Table 6 shows the debt at risk for the Chilean household sector in 2007 based in information of the SHF 2007. As before, we show the results by different income strata and, also, age strata. In the table we see that the debt at risk is increasing in the level of income. This means that

[22]See also Holló and Papp (2007) for debt at risk analysis.

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. In this sense, strata 3 bears a 12% of debt at risk in consumption debt, which represents nearly a 3% of the total debt. Strata 1 and 2, instead, possess 6% of the debt at risk in consumption and only a 1.5% 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. Households belonging to this group have a 8.7% of their consumption debt at risk, and therefore, this group is the riskier one. The range of age with lower debt at risk is that between 15 and 29 years old, mainly this is due to the fact that financial institutions do not grant them large amounts of credits.

In terms of aggregate level, the debt at risk in consumption debt reaches 18.4%, which is equivalent to 4.3% of the total debt. This level of DAR in consumption represents a non-negligible amount. In this sense, any deterioration in financial markets that affects households capability to pay could have important effects in this type of debt. However, in terms of total debt, the debt at risk is no so big but is something to take into account for future economic policies.

Table 6: Debt at Risk.

	% Indebtedness Households	% DAR in Consumption	% DAR in Total Debt
Stratum 1	44.91	1.98	0.46
Stratum 2	64.71	4.29	0.99
Stratum 3	65.56	12.13	2.80
Age 15-29	53.92	1.41	0.33
Age 30-44	65.52	6.77	1.56
Age 45-60	58.31	8.70	2.00
Age > 61	38.44	1.52	0.35
Total Households	54.97	18.40	4.24

Source: Authors' calculation.

6 Conclusions

We propose a new index to measure household's financial status. This index solves several problems presented in one of the main indexes used in the literature, the Debt Service to Income Ratio (DSR). Our new index, the MDSR, allows us to avoid the problems of treatment of outliers and, also, incorporates households without any transitory income. We show that the distribution of the MDSR is well behaved, which let us to focus on households with higher MDSR. These facts allow us to measure in a better way households in financial risk, and obtain unbiased results.

In order to understand the determinants of the household payment behavior, 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, meanwhile the MDSR and probability of layoff increases it. In particular, we show that the relationship between the probability of default and the MDSR is monotonically increasing. Also, we find that above a certain level of the MDSR (43% or a 75% of the DSR) it seems that the probability of default of a household do not increase. We believe that a household that reaches these levels of indebtedness is already in financial distress. 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, bear 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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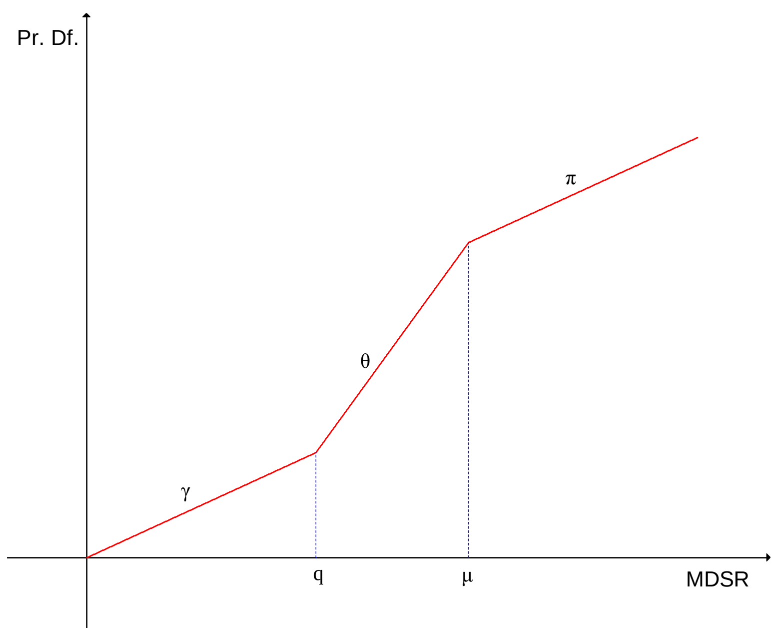
A MDSR Threshold

Some articles stress that above a certain DSR level, households increase substantially their probability of default, and therefore, households above this threshold are considered to be in financial distress (see for instance DeVaney, 1994; DeVaney and Lytton, 1995; Greninger et al., 1996; Karasulu, 2008; Faruqui, 2008; among others). The literature has been trying to find empirically whether this threshold exist or not through different estimation methods and allowing different functional forms (see for instance Del-Rio and Young, 2008; Dey et al., 2008). As the MDSR is directly related with the DSR, if there exist a threshold for the DSR, then we also expect to find it in the relationship between the probability of default and the MDSR.

In order to analyze this non-linear relationship, we use two dummies variables to build three different sections for the MDSR. Each dummy represents a threshold and each section has assigned a different slope. Figure B.1 shows the process decribed, where q and μ represent the lower and upper thresholds respectively and γ, θ and π represent the slope parameters associated with each section.

We test two thresholds to consider different households' behaviour as debt burden increases. This estimation strategy propose a richer structure compared to previous articles. In fact, this structure allows us to test not only the point where households are in distress (μ), but also we can test if there exist a point in which the debt burden becomes a problem to households' financial position (q).

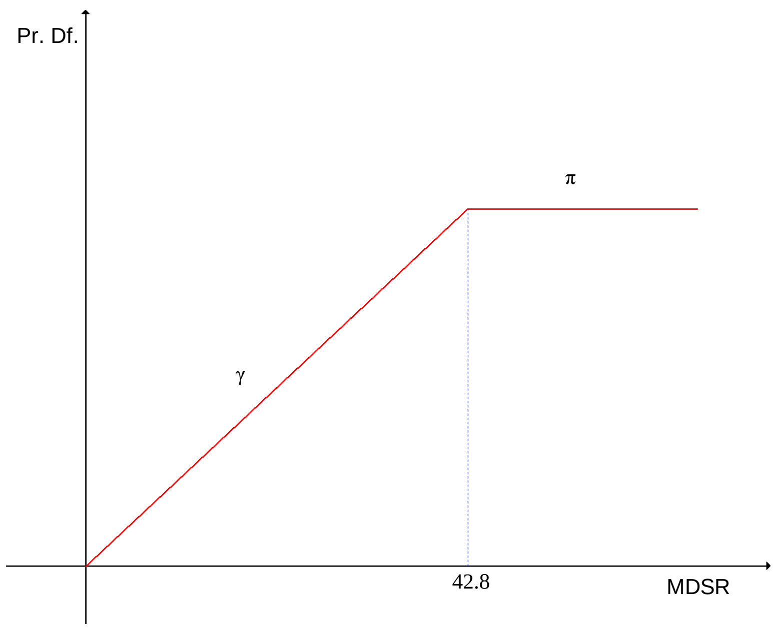
Figure B.1: MDSR and probability of default relationship.



We perform several estimations of our probit equation 3, changing both thresholds through the MDSR domain. We estimate all the possible combinations for both thresholds making changes of 5% on each one at the time. For each estimation we test the statistical significance of the parameters associated to each slope. The final specification contains only one threshold at a 42.8% of the MDSR, which is equivalent to a 75% of the DSR. In terms of the slope, we find one significant slope between 0 and 42.8% of the MDSR. Above this threshold we do not find a significant slope, therefore, we use a dummy variable to capture this fact, which take the value one when the MDSR is over the 42.8%.

Figure B.2 shows the final estimated relationship between MDSR and the probility of default, which is related to estimation of the probit in table 4. In this specification, the dummy variable is not significant, which reflects that increases in MDSR over the threshold do not increase the probability of default.[23]

Figure B.2: Final specification between the MDSR and the probability of default.



In constrast to Dey et al. (2008), we do not find a certain value for the MDSR (DSR) where above it the probability of default increases significantly. Instead, we find a monotonically increasing relationship between the MDSR and the probability of default, similar to Del-Rio and Young (2008) but using a more flexible specification. However, in contrast to their result, we find that having an MDSR (DSR) over this threshold does not increase household probability of default.

[23] Approximately 7% of the sample has an MDSR over the threshold.

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