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Abstract

Global trends show high levels of households' indebtedness, not seen before, in developed and emerging economies that could affect countries' financial stability. This paper develops an approach based on market aspects to estimate households' debt thresholds, applicable to any economy where household financial survey and interest rate ceilings exist. We use statistical information from the 2017 Chile's household financial survey. The results state that: The same debt threshold should not be used for all households as variables such as income affect it. Both short-term and long-term debt thresholds increase with households' income level. The presence of mortgage debt increases debt thresholds.

Keywords: debt thresholds, FBTI, DTI, approach, over-indebtedness

JEL Classification: C51, C58, D14, G21, G28

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1 Introduction

Global trends show household indebtedness levels not seen in past decades (Institute of International Finance, 2019). Indeed, international economic organizations such as the IMF and the OECD, in their flagship publications "Global Financial Stability Report" and "Economic Outlook", express their concerns about the level of households' indebtedness both in developed and emerging economies.[1]

In economic or financial stress, a high level of households' indebtedness could lead to higher credit risk that could affect the country's financial stability.[2] Hence, carrying out appropriate monitoring of households' indebtedness through debt indicators and their thresholds is necessary to identify over-indebtedness and greater credit risk.

This papers' goal is to determine households' debt thresholds. Using debt thresholds without methodological support or not considering the specificities of the economy of study could generate effects contrary to the desired goal. In fact, without an adequate diagnosis of over-indebtedness, public policies may not generate the desired result.[3]

We propose a novel approach based on market aspects, differing from traditional methods - based on statistical characteristics and households' perception of over-indebtedness - used in the banking industry and the literature. We identify households' debt thresholds for the

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[1] International Monetary Fund, 2017, "Global Financial Stability Report October 2017" (Washington D.C.). Organization for Economic Co-operation and Development, 2017, "OECD Economic Outlook", Volume 2017 Issue 2, (Paris).

[2] Credit risk is the financial risk associated with losses that a lender may incur if the debtor does not meet the defined payment conditions. In other words, it corresponds to the risk incurred by the lender if he is unable to recover, from the debtor, the credit amount and its interests.

[3] For example, using an indebtedness threshold lower than that consistent with the state of economy could overestimate households' indebtedness. Contrary, a debt threshold higher than reasonable could state a healthy level of indebtedness that is not.

debt indicators - the household financial burden to income ratio (FBTI) and household debt to income ratio (DTI) - at the aggregate level and contingent to income level.[4]

The approach developed applies to economies where households' financial survey and interest rate ceiling exist. Many economies (about eighty), from different geographical areas and varying development levels, use interest rate ceilings (Munzele and Henríquez, 2014; Ferrari et al., 2018).

In this paper, we study the case of Chile as it has the most indebted households in Latin-American, with 44% of the country's GDP in 2019 (International Monetary Fund, 2019) and households' debt growing about 7% in recent years (Central Bank of Chile, 2018). Also, in Chile, its Central Bank produces a household's financial survey, and the financial market regulator sets interest rate ceilings. Both critical pieces of information to develop the approach we propose.

The literature using households' financial surveys to study households' indebtedness includes early contributions from authors such as Johansson and Persson (2006), Vatne (2006), Del-Río and Young (2008), Dey et al. (2008), and Michelangeli and Pietrunti (2014) for Sweden, Norway, the United Kingdom, Canada, and Italy. In the case of Chile, the literature includes contributions investigating households' indebtedness without identifying debt thresholds (Alfaro and Gallardo, 2012; Ruiz-Tagle et al., 2013; Central Bank of Chile, 2019) or calculating debt thresholds but at the aggregate level (Martínez et al., 2013; Córdova and Cruces, 2019; and Cifuentes et al., 2020). Thus, in this paper, we contribute to the literature by developing a novel approach based on market aspects and calculating debt thresholds considering households' income levels.

The main results state that:

[4] The FBTI and the DTI are debt indicators that compare the levels of debt and income during a given period, popular in the banking industry and the literature, and complementary as the FBTI quantifies short-term debt and the DTI identifies long-term debt.

i. The FBTI threshold increases with the households' income. The FBTI threshold increases with the households' income. In particular, among the households not having mortgage debt: those earning the monthly minimum wage (320 thousand Chilean pesos, about USD 400) have an FBTI threshold of 6%; and that those with a very high monthly income (3 million Chilean pesos, about USD 4,000), we see an FBTI threshold of 37%. On its hand, among households having mortgage debt, while those earning the monthly minimum wage find an FBTI threshold of 26%, those earning ten times the monthly minimum wage have an FBTI threshold of 60%.

ii. The DTI indicator also observes debt thresholds that increase with the households' income.

iii. The debt thresholds, measured by the FBTI and the DTI, increase when the household has mortgage debt.

iv. In Chile, short-term debt (high monthly income burden) explains its households' indebtedness due to the extensive use of credit cards and credit lines.

The rest of this paper includes the following sections. Section 2 presents the data (2017 Chile's household financial survey) and the indebtedness ratios (FBTI and DTI) we use. Section 3 discusses the existent approaches in the literature estimating households' debt thresholds and their drawbacks. In Section 4, we present our approach - based on market aspects - to determine households' debt thresholds. Section 5 discusses the results using the approach presented in Section 4. Finally, Section 6 concludes.

2 The households' financial survey and the ratios of indebtedness

In Chile, its Central Bank carries out the households' financial survey since 2007, aiming to collect financial data from Chilean households, and generating detailed information on their income and expenditure. Here we use the most recent households' financial survey (HFS2017) as it provides disaggregated information on different types of households' debt not available in previous versions.

The HFS2017 has twelve thematic modules, each designed to test a specific financial aspect. Table 1 presents the detail of these modules and the corresponding categories.

Besides having financial information from the Chilean households, the HFS2017 provides expansion factors allowing weighting their observations and making unbiased estimates of population parameters.[5]

Regarding indebtedness ratios, while the banking industry uses them to monitor customers' credit risk, regulators and other public institutions consider them a tool for financial stability monitoring. The ratios of indebtedness are indicators relating debt to income or assets (in this paper of a household), allowing indebtedness evaluation.[6] In general, a ratio of indebtedness follows equation (1).

$$ratio\ of\ indebtedness_{i,t} = \frac{debt_{i,t}}{income_{i,t}} \tag{1}$$

[5] The expansion factors correspond to the number of households represented by the household surveyed in the HFS2017.

[6] For example, in the European Union, its members use indebtedness ratios to measure systemic risk, setting different limits depending on characteristics such as the level of income and type of credits.

Where, $debt_{i,t}$ is a measure of indebtedness of a household "i" in a period "t", and $income_{i,t}$ is a measure of the income of a household "i" in the same period "t".

The EFH2017 reports the FBTI and the DTI.[7] The FBTI is an indicator that allows assessing the percentage of monthly income that a household must spend to pay its credit obligations. Thus the FBTI relates the household financial burden with its monthly income (equation (2)). The financial burden is the monthly amount that a household must pay in debts, including the interests. So the FBTI is a measure of short-term indebtedness.

$$FBTI_{it} = \frac{financial\ burden_{i,t}}{monthly\ income_{i,t}} \tag{2}$$

Meanwhile, the DTI allows quantifying how massive a household's total debt is to its income. Then, the DTI relates the total amount of a household debt (excluding the interests) to its income (equation (3)). Thus the DTI is a measure of long-term indebtedness.

$$DTI_{it} = \frac{debt_{i,t}}{annual\ income_{i,t}} \tag{3}$$

Different definitions of debt and household income exist (D'Alessio and Iezzi, 2013).[8] Meanwhile, in the case of debt, the usual distinction is between guaranteed and unsecured debt; in the case of income, the difference is between gross and disposable income. The secured debt is usually associated with mortgages, and the unsecured debt relates to consumer loans.

[7] We also have information on the debt to assets indicator, but we decided not to include it due to assets valuation difficulty.
[8] Further detail on definitions of over-indebtedness and debt ratios in Betti et al. (2007) and European Commission (2008).

3 Drawbacks of the existent approaches

Alternative approaches to estimate households' debt thresholds exist in the literature. The most popular are: the statistical method (Dey et al., 2008; Martínez et al., 2013; Michelangeli and Pietrunti, 2014; Córdova and Cruces, 2019) and the approach based on households' perception of over-indebtedness (Del-Río and Young, 2008; D'Alessio and Iezzi, 2013; Cifuentes et al., 2020).

In the statistical approach, households' indebtedness becomes unsustainable when there is an abrupt break or a structural change in the probability of default (Dey et al., 2008; Martínez et al., 2013). To test the statistical approach, we replicate it using data from the HFS2017 and provide rates of default and ratios of indebtedness for all households (Appendix A). The results suggest that while the statistical approach benefits from simplicity, it also has negative aspects, such as non-monotonic functions that cannot find a single threshold. Thus the threshold found may be arbitrary and lead to a lack of statistical robustness.

On its hand, D'Alessio and Iezzi (2013) propose an approach based on households' perception of over-indebtedness, consisting of maximizing the correlation between over-indebtedness and the economic distress of household debt. We replicate the method proposed by D'Alessio and Iezzi (2013) using the HFS2017, finding no robust results (Appendix B). Even so, D'Alessio and Iezzi (2013) point out that their economic distress measure is subjective, has limitations, and is an imperfect metric of over-indebtedness.

4 Methodological proposal

This section proposes an approach based on market aspects to determine households' debt thresholds at the aggregate level and depending on households' income level. The motivations for the approach we propose are: the technical objections to the methods discussed in Section 3; that even ignoring the technical objections, the existent techniques cannot provide robust debt thresholds; and the need to define debt thresholds contingent on the households' level of income (Martínez et al., 2013; Córdova and Cruces, 2019; Cifuentes et al., 2020).

The approach we propose considers five steps:

i. Decide on the definition of over-indebtedness to use.

ii. Develop a model of probability of default, based on the FBTI and the income level.

iii. Define the characteristics of the average debtor household.

iv. Determine the banking system's implicit lending interest rate, based on the average debtor household characteristics (step (ii)) and the different FBTI and income levels.[9]

v. And, find for each income level the maximum FBTI so that the implicit lending interest rate is lower than the interest rate ceiling, defined by the financial regulator.

In short, the approach we propose seeks to determine the maximum FBTI for which the banking system offers an implicit lending interest rate lower than the interest rate ceiling. Hence, if the FBTI is above the debt threshold, the debtor would be more risky, leading to a higher implicit lending interest rate, which would not be feasible due to the restriction that the interest rate ceiling imposes.

[9] We understand the implicit lending interest rate as the maximum interest rate with which the credit is granted. To obtain the implicit lending interest rate, we must know the probability of default estimated in step (ii).

The treatment proposed for the FBTI can also apply to the DTI. Indeed, by consolidating the total household debt, the proposed approach generates simultaneous thresholds for the FBTI and the DTI due to the formula of "French depreciation" that produces a linear relationship between the quota and debt - dividing by the income results in a direct relationship between the two ratios (see equation below).

$$Quota = Debt \cdot \frac{(1+rate)^{credit\_period} \cdot rate}{(1+rate)^{credit\_period} - 1} \tag{4}$$

Usually, regulators set interest rate ceilings to delimit usury, protecting consumers from excessive interest rates. Many economies (about eighty) from different geographical areas and varying development levels use this type of regulatory instrument (Munzele and Henríquez, 2014; Ferrari et al., 2018). Hence the approach we propose might be applicable in those economies.

In summary, the approach proposed has the advantage of establishing thresholds of indebtedness that are intuitive, based on market information, and applicable in economies where households' financial surveys and interest rate ceilings exist.

4.1 Definition of over-indebtedness

Due to various and different criteria and definitions of over-indebtedness, the European Commission in 2010 (European Commission, 2010) set specific guidelines for its members, which we decided to follow. These guidelines establish that over-indebtedness:

i. Has to be measured at the household level.

ii. Must include all types of credit.

iii. Is the inability to cover recurring expenses.

iv. Requires a household to reduce its expenses or find ways to increase its income to fulfill its financial commitments.

v. Is the position in which it is not possible to solve the problem through new loans.

To meet these guidelines, we calculate indebtedness ratios using the HFS2017, understanding over-indebtedness as "the situation in which households cannot consolidate their debt acquiring more loans from the banking industry".

4.2 Probability of default

In this subsection, we develop a probability of default model to quantify credit risk. In general, the probability of default is a single parameter that depends on the credit applicant's specific characteristics, determining how likely it will pay back (López et al., 2018).

Many approaches exist to estimate the probability of default (Lessmann et al., 2015), and nonlinear econometric models are the most common (López et al., 2018). Among this type of model, the most used is the probit model, which describes an event with two possible outcomes, such as fall into default or not. To get the probability of default, we assume a standard normal distribution, estimate coefficients, and use the cumulative inverse function of distribution (Φ), described in equation (5).

$$P(default = 1|X) = \Phi(\beta X) \quad (5)$$

To estimate each household probability of default, we define a binary variable indicating the occurrence of default, based on the households' responses in the HFS2017. Table 2 presents the variables used to calculate households' probability of default, using the probit model.[10]

Table 3 presents the results for all households and those without mortgage debt. Both models include the FBTI instead of DTI because its polynomial generates greater statistical significance.

To model households' payment behavior for those without mortgage loans, we use the second column of Table 3. The third column model - estimated for all households - provides the households with mortgage loans. Unfortunately, we cannot directly study households' behavior with mortgage loans because we find a statistically not significant parameter for this model's variable income. Such a result could be explained because financial institutions offering mortgage loans precisely grant their credit by filtering debtors using income as the primary explanatory variable.

We have that the variables "education" and "age" have negative coefficients. In other words, a more educated person should have greater financial literacy and access to better wages, reducing her probability of default. Also, the older a person, the more exceptional ability she has to meet her credit obligations.

Moreover, the variable "employed" has a positive coefficient. It suggests that the more persons contributing to the household income, the higher the probability of default, result unexpected. Meanwhile, the variable "members" reports an intuitive positive coefficient as the more members in the household, the more challenging it to fulfill their financial obligations.

[10] We also estimated a logit model, finding similar results to those of the probit model. However, the results of the probit model were more satisfactory - more significant R^2.

Finally, the FBTI finds a positive coefficient. It is a result intuitive, which means that the bigger the FBTI, the higher the probability of default. Then nonlinear versions of the FBTI also obtained significant coefficients.

4.3 Characteristics of the average debtor household

Table 4 shows the characteristics of the average Chilean household. In summary, households tend to have more years of education and younger if they have a mortgage loan, and the number of members and the members employed is about the same whether the household has a mortgage loan or not.

4.4 The implicit lending interest rate

Lenders have three mechanisms to protect themselves from credit risk. First, the amount of credit granted; second, the credit maturity; and third, the credit interest rate, known as the implicit lending interest rate. If a lender considers risky a credit applicant, the amount granted will be less than for an applicant who does not represent a high credit risk. The higher the risk, the shorter the period in which the debtor has to settle the credit. So the more significant the credit risk, the debtor has to pay the credit before. Finally, the higher the applicants' credit risk, the lender will compensate that risk with a higher implicit lending interest rate.

We assume that the lender adjusts the borrower credit risk through the implicit lending interest rate. It is a simplified abstraction of the reality that would solve the bank's problem. Evidence suggests that the higher the borrower credit risk, the lender tends to offset that risk with a higher implicit lending interest rate (Pulgar and Rojas, 2019). Also, we assume that the period to pay the loan is equal to the average period for the same type of credit in the banking system.[11]

The lending interest rate for a credit applicant "i" corresponds to the sum of two components, the credit risk-free interest rate and the credit risk premium. The credit risk-free interest rate represents the charges in which a lender incurs to cover the administrative and financing costs of providing credit, being the same for all the lenders' clients. Thus, the credit risk-free interest rate does not depend on the credit applicant's characteristics. However, the credit risk premium depends on the credit risk and the applicant characteristics, hence its complexity.

We consider both the administrative costs (3% is the average for the Chilean banking system) and the cost of financing to calculate the credit risk-free interest rate. As established by the Basel Committee in its Internal Risk-Based standard, the capital required differs depending on if the transaction has a mortgage or does not. The capital required will also depend on the probability of default and the average portfolio loss given default (LGD), where mortgage loans find lower values due to a guarantee (collateral).[12]

Besides, we assume that debt consolidation occurs through banks as the interest rates offered to the same debtor would be lower than those by the NBCIs. Banks have lower financing costs due to the greater relevance of deposits within their liabilities and significant scale economies in administrative costs.

Mortgage loans could associate their financing with a bond or similar instruments due to their structure of flows and duration. Nevertheless, we prefer assuming their financing through

[11] Based on Chile's financial regulator's information, for the period 2016 – 2019, we assume 35 months for consumer loans and 22 years for mortgage loans.

[12] The LGD corresponds to the losses incurred by the lender in case the debtor defaults.

liabilities, particularly to term deposits, as these constitute the majority of mortgage funding. The average cost of financing through capital is 12%, and 3% through liabilities.[13] Following the procedure described, we find a risk-free interest rate of 5.65% for debtors with mortgage loans and 7.8% for debtors without them.

To calculate the credit risk premium, we follow equation (6), which requires knowing the credit risk-free interest rate and specific risk parameters.

$$\sum_{i=1}^{N} \frac{\mathbb{E}_0[c(r^{lrc} + prc)\,]}{(1 + r^{lrc})^i} = \sum_{i=1}^{N} \frac{c(r^{lrc})}{(1 + r^{lrc})^i} \tag{6}$$

Where, r^{lrc} is the risk-free interest rate, prc is the credit risk premium, $\mathbb{E}_0[.]$ corresponds to the expectation conditional to the information available when granting the credit, $c(.)$ is the value of the quota related to a specific lending interest rate, and N is the number of allocations up to maturity.[14]

We calculate the debtor probability of default following the procedure described in subsection 4.2. For the LGD, we consider the Financial Market Commission (CMF) values in its standard model of provisions (Financial Market Commission, 2019) when a mortgage has a guarantee and a value of 61.3% if it is not the case.[15]

Note that if a household has a mortgage loan or not, considerable differences exist among the banking system's interest rates because of the reduced capital requirement and the

[13] We calculate these costs by using information from Chilean banks. This information reported to Chile's financial regulator considers the period around the HFS2017, meaning between January 2016 and May 2018.
[14] For simplicity, hereafter, we use the annual rates.
[15] This value comes from estimates based on the Chilean banks' information provided to the CMF for consumer loans.

lower credit risk premium due to the existence of a guarantee. Then, by methodological construction, we find different debt thresholds for those households with and without mortgage loans. Such a finding is consistent with the literature and the regulations in different economies.

4.5 The interest rate ceilings

To determine when households' indebtedness becomes unsustainable, we assume that it corresponds to the debt whose implicit lending interest rate, consistent with the debtor risk, is higher than the interest rate ceiling. In Chile, the interest rate ceiling differs depending on the currency, type of loan, amount, and credit maturity. This paper uses an interest rate ceiling in Unidades de Fomento (UF) for mortgage loans and an interest rate ceiling in "Chilean pesos" when it is not the case.[16] [17] The interest rate ceiling in UF is about a real 5 %, and the interest rate ceiling in Chilean pesos is about a nominal 34% (see Appendix C).

5 Results

This section provides the results using Section 4, first presenting aggregate households' debt thresholds and then considering households' income level, providing individual households' debt thresholds. The presentation and comparison of both results allow observing how the income level affects the households' debt thresholds.

[16] The UF is a unit of account used in Chile to adjust by inflation.
[17] We use the highest interest rate ceiling (in pesos, credit maturity equal or higher than 90 days, and amount lower than 200 UF) as credit loans in installments might have different interest rate ceilings. Then, the highest interest rate ceiling relates to credit loans of 50 UF or less. We also assume that debt restructuration occurs through different small loans if the household's total debt exceeds 50 UF. This assumption generates the benefit of developing a single threshold for all debtors who do not have a mortgage loan. Otherwise, depending on the total debt, different thresholds could exist.

Our estimates also include a spread representing the banking industry's profits or the costs to cover other risks not considered in the modeling. Pulgar and Rojas (2019) suggest that risk aversion, liquidity premium, and rents due to imperfect competition could explain such spread.

On the one hand, for the portfolio of consumer loans, which we relate to those debtors without mortgage loans, we find a spread of 3.8% per year. Moreover, we find a spread of 3.6 basis points for the mortgage loans portfolio. The big difference between these two spreads might relate to banks' higher bargaining power over customers in consumer loans than in mortgage loans. In the latter case, the debtor tends to consider a higher number of alternatives due to the loan size.[18]

5.1 Aggregate debt thresholds

Omitting households' specific variables such as their income level generate aggregate and unique household debt thresholds for indebtedness ratios. Figures 1 and 2 show the households' aggregate debt thresholds. The X-axis reports the maximum FBTI consistent with an implicit lending interest rate plus the spread (for the average portfolio) lower than the interest rate ceiling.

Figure 1 shows that the aggregate debt threshold (maximum FBTI) for households without mortgage loans, consistent with an implicit lending interest rate plus the spread (for the average portfolio) lower than the interest rate ceiling of 34%, is 25%. Furthermore, without the spread, the maximum FBTI is 36%.

[18] To better understand the effect of bargaining power in financial contracts, review the contract theory in Rudolph (2006).

The case for households having mortgage loans (Figure 2) observes a minimal spread (for the average portfolio). The lower interest rate ceiling and implicit lending interest rate, consistent with the smaller risk due to a guarantee, imply a maximum FBTI equal to 52%. Without the spread, the maximum FBTI should be 51%.

Considering the definition of over-indebtedness used in this paper and equation (6), from the FBTI threshold, it is also possible to get the DTI threshold. These results suggest that for households' debtors without mortgage loans, the DTI threshold is six times the monthly income, and for debtors with mortgage debt, it is 71 times the monthly income.

The FBTI thresholds of 23% and 51% for debtors with and without mortgage loans are consistent with what D'Alessio and Iezzi (2013) found for Italy. Ruiz-Tagle et al. (2013) find a DTI threshold of six times the monthly income in Chile. In sum, we find that households holding mortgage debt have a higher DTI threshold than those without this type of debt.

5.2 Individual debt thresholds

This subsection repeats subsection 5.1 analysis but considers the households' income level, thus modifying the probability of default, adjusting the credit risk premium, and the implicit lending interest rate. Such a modification allows finding individual households' debt thresholds contingent on their level of income.

Authors such as Ruiz-Tagle et al. (2013) and Córdova and Cruces (2019) highlight the importance of income in determining debt thresholds. According to Ruiz-Tagle et al. (2013), although income normalization in indebtedness ratios exists, a decreasing marginal propensity to consume could imply higher debt thresholds for households with higher income. Córdova and Cruces (2019) point out that it would be informative to complement the standard debt indicators with an extra dimension, such as the level of income, as the evidence indicates that debt thresholds are not the same for all households. Figures 3 and 4 present the results following the approach proposed, showing that debt thresholds indeed are susceptible to the households' level of income.

Figure 3 shows that for debtors without mortgage loans, the debt threshold could be lower than 6% for those households earning a monthly income close to the minimum wage (320 thousand Chilean pesos, about USD 400), and higher than 37% for those households having a monthly income above 3 million Chilean pesos (about USD 4,000). When considering the income level, the approach proposed delivers debt thresholds contingent on income level, describing a logarithmic relationship between the FBTI threshold and income level. This result is consistent with the limits set by members of the European Union for the measurement of systemic risk (European Systemic Risk Board, 2019), as the higher the income of a debtor, the higher the possibility of allocating a larger fraction of revenue to the payment of financial services.

Figure 4 shows the results for debtors with mortgage credit. Among households having mortgage debt, while those earning the monthly minimum wage find an FBTI threshold of 26%, those earning ten times the monthly minimum wage have an FBTI threshold of 60%.

As mentioned, it is possible to generate DTI thresholds through the relationship described by equation (4). For example, among the households without mortgage debt: those earning the monthly minimum wage (about USD 400) have a DTI threshold of 1.5 times, and those earning a high monthly income (about USD 4,000) have a DTI threshold of 8.9 times. Appendix D presents in detail the results in Figures 3 and 4.

From our results, we infer the following relationships for the FBTI and the DTI:

i. A household without mortgage credit is over-indebted if:

$$FBTI > 13.29\% \cdot ln(Income) - 1.6174 \;\; or \; DTI > 3.2162 \cdot ln(Income) - 39.134$$

ii. A household with mortgage credit is over-indebted if:

$$FBTI > 15.29\% \cdot ln(Income) - 1.6829 \;\; or \; DTI > 21.347 \cdot ln(Income) - 234.946$$

iii. In any other case, the household would not be over-indebted

The approach proposed establishes a relationship between the FBTI and the DTI by using the total consolidated debt in credit with installments. Nevertheless, debtors may have liability on various financial products with different characteristics (credit cards, credit lines, loans with installment, student loans, and mortgage loans). Thus, we propose to use both metrics (FBTI and DTI) for the definition of over-indebtedness.

If we apply these relationships above to the Chilean population, using the EFH2017 and its corresponding expansion factors, we find that 44.5% of households would be over-indebted. Table 5 shows the breakdown of the cause of the over-indebtedness, where the figures in italic highlight the percentage of households that would be over-indebted in each case.

Table 5 shows that 26.7% of households would be over-indebted in the short term ($\mathrm{FBTI} > \mathrm{FBTI}^*$) but not in the long term (DTI). Meanwhile, only 1.9% of households would be over-indebted in the long run ($\mathrm{DTI} > \mathrm{DTI}^*$), without being under a high monthly financial burden (FBTI). This result would show that a high monthly income burden would explain indebtedness in Chile, i.e., short-term indebtedness. The extensive use of credit cards and credit lines, to their income, in Chile might explain such result.

6 Conclusions

Households have sharply increased their debt level in recent years, a phenomenon observed in developed and emerging economies. Unfortunately, the existing methodologies for determining households' debt thresholds of sustainability indebtedness have some weaknesses and do not differentiate among essential characteristics, such as income level.

This paper proposes an approach to determine debt thresholds, both at the aggregate level and contingent to the households' level of income, applicable to any economy where households' financial data and interest rate ceilings exist. Indeed, we calculate households' debt thresholds for the ratios of indebtedness (the financial burden to household income ratio (FBTI) and debt to household income ratio (DTI)), using Chile's Households Financial Survey of 2017.

The approach proposed generates results consistent with the thresholds used in the banking industry and the literature. We find that debt thresholds increase in the households' income level, differing depending on whether they are mortgage debtors or not. Using a single threshold of over-indebtedness would imply that some low-income debtors would not be considered over-indebted. In contrast, some high-income debtors could be regarded as over-indebted without being over-indebted. The thresholds for the ratios of indebtedness (FBTI and DTI) are increasing in the level of income.

Some difficulties exist in the implementation of the approach proposed:

i. Despite having complete information about debtors' loans, lenders could not know their characteristics, creating difficulties in calculating the monthly payments. Thus the financial burden calculation is challenging.

ii. Lenders could face the challenge of identifying whether a debtor is over-indebted or not, and then the recommendation is using the most recent credit applicant income information.

iii. In general, lenders and regulators do not have access to the data of all loans in the market. Consolidated debt information would allow avoiding this inconvenience.

Finally, it is possible to extend the proposed approach by considering specific probabilities of default for each debtor, thereby affecting its implicit lending interest rate. Even though this refinement would generate a more accurate metric, it also is more challenging to apply.

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Table 1. Modules and categories in the HFS2017

Module	Category
A	Household composition
B	Education
C	Employment status
D	Payment methods
E	Real assets and mortgage debt
F	Non-mortgage debt
G	Perception of a financial burden and credit restrictions
H	Vehicles and other real assets
I	Financial assets, pensions, and insurance
J	Related incomes
K	Future incomes
L	Other revenues and non-related incomes

Source: Central Bank of Chile.

Table 2. Variables included in the probability of default model

Variable	Description
Default	A binary variable that takes value one if the household has declared that it has paid less than the least on any credit card or is not paying a consumer credit debt with banks or non-bank credit institutions. The analysis for mortgage debt has this type of loan debt included in the default. We excluded student loans.
Education	Years of education by the person of the household answering the survey.
Age	Age of the person of the household answering the survey.
Employed	Number of persons employed in the household and contributing to the household income.
Members	Number of members in the household.
FBTI	Ratio of the financial burden to household income.
$FBTI^2$ and $FBTI^3$	The square and cube of the FBTI. The inclusion of these variables allows assessing the nonlinear relationship between the FBTI and the default behavior.
ln(toth)	Natural logarithm of the total monthly household income.

Source: Authors' elaboration based on HFS2017.

Table 3. Probability of default model

Variables	Households without mortgage debt		All households with debt	
Intercept	1.35	*	-1.23	**
Education	-0.03	***	-0.04	***
Age	-0.01	***	-0.01	***
Employed	0.11	**	0.12	***
Members	0.07	***	0.06	***
FBTI	1.01	***	0.78	***
$FBTI^2$	-0.16	***	-0.09	***
$FBTI^3$	0.01	***	0.002	***
ln(toth)	-0.12	**	-0.11	***
R^2 of Nagelkerke	0.106		0.096	
N° of observations	1,820		3,015	
	(2,131,073)		(3,164,591)	

Source: Authors' elaboration.
Note: *, **, and *** show statistical significance at 10%, 5%, and 1%. In parentheses, the number of households in each regression after using the expansion factors.

Table 4. Characteristics of the average debtor household

Variables	Households without mortgage loans	Households with mortgage loans
Education	12.6	15.4
Age	48.5	44.6
Employed	1.6	1.7
Members	3.4	3.4

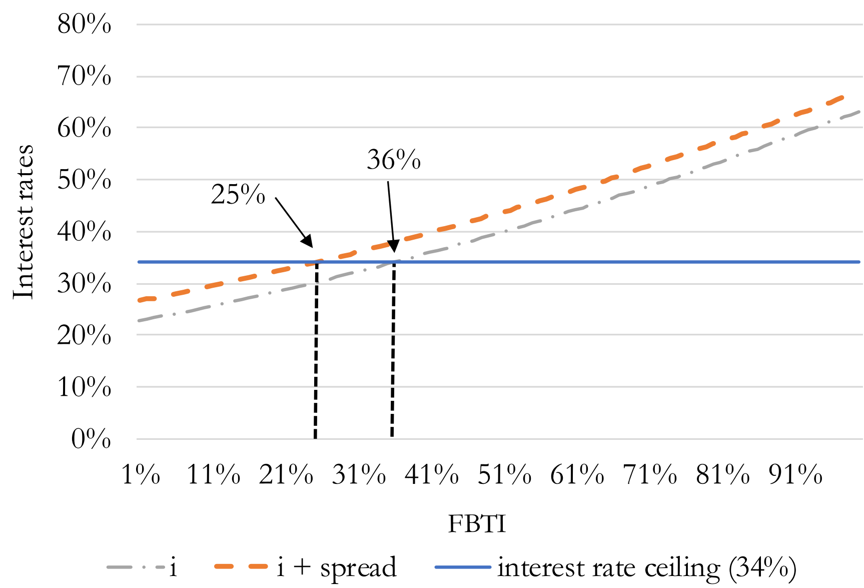
Source: Authors' elaboration.

Table 5. Households' over-indebtedness in Chile

	$\mathrm{DTI} \leq \mathrm{DTI}^*$	$\mathrm{DTI} > \mathrm{DTI}^*$
$\mathrm{FBTI} \leq \mathrm{FBTI}^*$	55.5%	*1.9%*
$\mathrm{FBTI} > \mathrm{FBTI}^*$	*26.7%*	*15.9%*

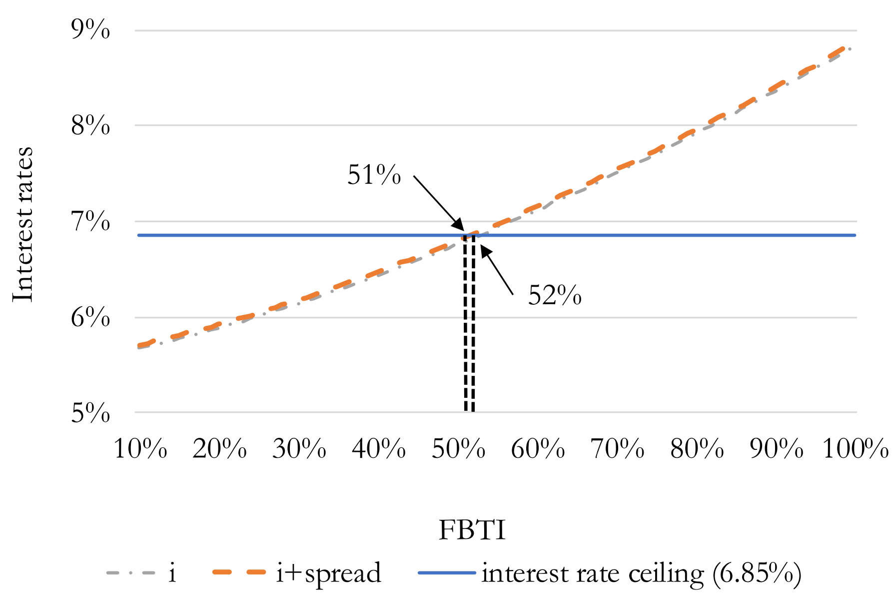
Source: Authors' elaboration based on HFS2017.
Note: DTI* denotes the debt to income threshold, and FBTI* represents the threshold for the financial burden to income.

Figure 1. Aggregate debt thresholds for households without mortgage loans



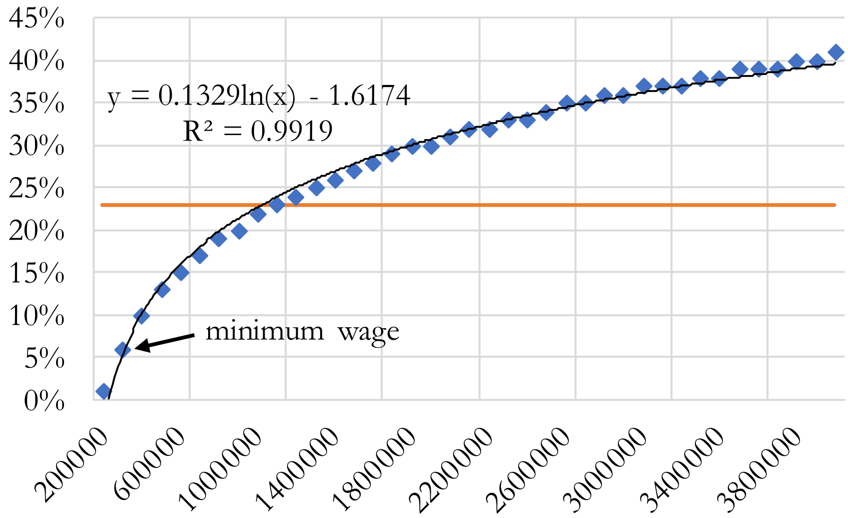
Source: Authors' elaboration based on HFS2017.
Note: "i" denotes the implicit lending interest rate.

Figure 2. Aggregate debt thresholds for households with mortgage loans



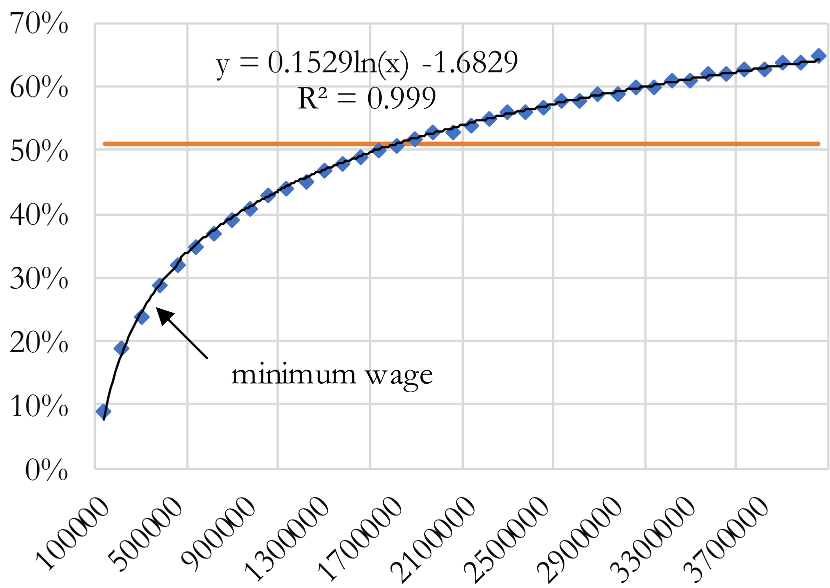
Source: Authors' elaboration based on EFH2017.
Note: "i" denotes the implicit lending interest rate.

Figure 3. Individual debt thresholds (FBTI) for households without mortgage loans and considering their level of income



Source: Authors' elaboration based on HFS2017.
Note: The bold line represents the unique FBTI threshold of 23% when not considering income level. The dots represent the individual debt thresholds, considering the households' level of income. FBTI (Y-axis) and Chilean pesos (X-axis).

Figure 41. Individual debt thresholds (FBTI) for households with mortgage loans and considering their level of income



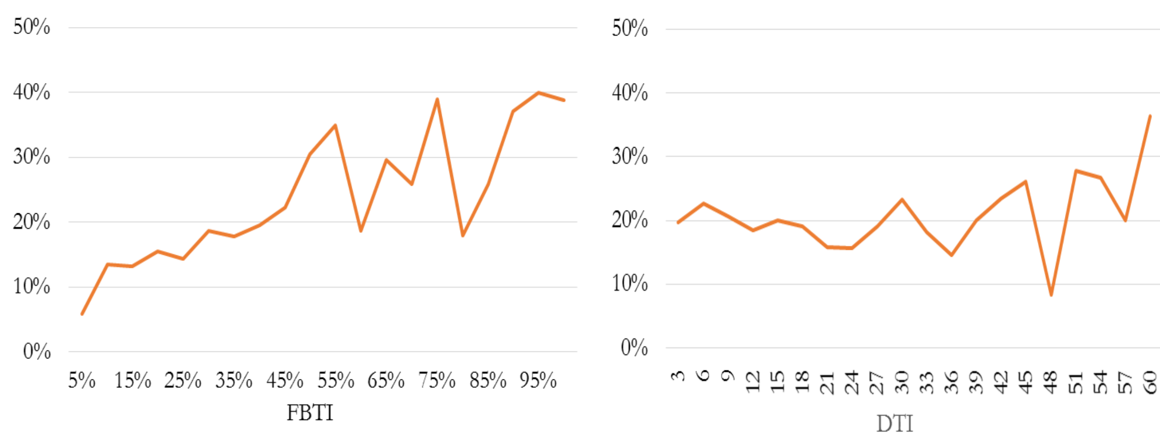
Source: Authors' elaboration based on HFS2017.
Note: The bold line represents the unique FBTI threshold of 23% when not considering income level. The dots represent the individual debt thresholds, considering the households' level of income. FBTI (Y-axis) and Chilean pesos (X-axis).

Appendix

A Statistical approach

This appendix replicates the statistical approach, proving evidence suggesting that whatever the threshold found may be arbitrary and lead to a lack of statistical robustness. To do so, we use the data from the HFS2017, presenting rates of default and ratios of indebtedness for all households. According to the statistical approach, households' indebtedness becomes unsustainable when there is an abrupt break or structural change in the probability of default (Dey et al., 2008; Martínez et al., 2013).

Figure A. Rates of default and ratios of indebtedness for all households



Source: Authors' elaboration based on HFS2017.
Note: Y-axis (rates of default), X-axis (ratios of indebtedness).

Figure A observes default rates that increase significantly after an FBTI of 45% and without a clear pattern for the DTI. The functions obtained not only do not observe monotonicity, but also the FBTI threshold seems high compared to those used in the banking industry (30%), and the literature (Tiongson et al. (2010) and Michelangeli and Pietrunti (2014) use a threshold of 30%. Dey et al. (2008) suggest 35%).

A possible explanation for the lack of monotonicity in the functions we obtained is that indebtedness ratios affect credit risk. However, credit risk also is affected by other variables (Madeira, 2019). Even more, Córdova and Cruces (2019) propose that jointly the ratios of indebtedness and the level of income explain default, being necessary to control accordingly.

B The approach based on households' perception of over-indebtedness

Authors, as D'Alessio and Iezzi (2013) propose an approach that consists of maximizing the correlation between a household over-indebtedness and the economic distress about its debts.[19] The inconvenience with this approach is that the financial distress measure used is subjective. The thresholds we found using the HFS2017 are not robust and do not generate reliable results.

This appendix replicates D'Alessio and Iezzi (2013) approach using the HFS2017, as it includes the question: "Taking into account all the household debt: How would you rate the level of your household indebtedness?" The answers available are 1. Excessive, 2. High, 3. Moderate, and 4. Low. Table B shows the results for indebted households.

Table B. Households' perception of indebtedness

Answer	Participation
Excessive	11%
High	24%
Moderate	46%
Low	19%

Source: HFS2017.

[19] Besides, these authors propose alternative indebtedness metrics, noting that for the FBTI, the most common threshold is 30% for all debts and 25% for unsecured debts only.

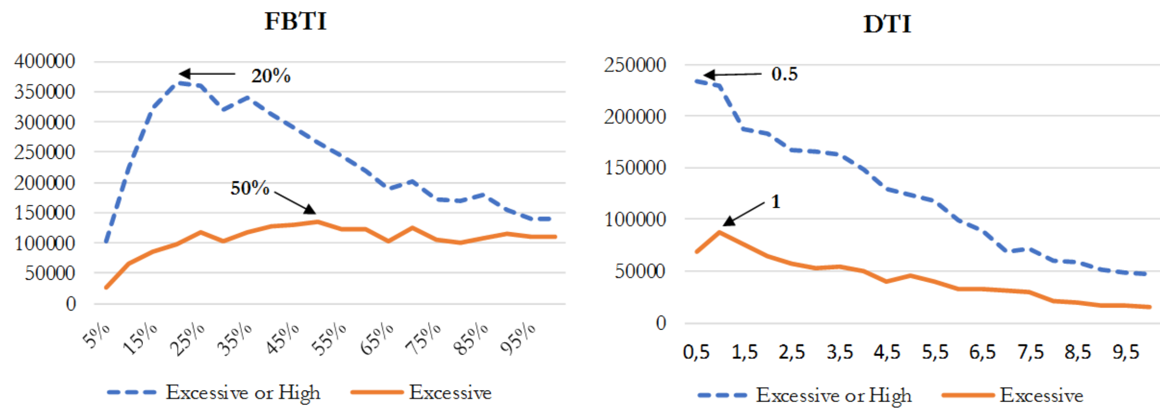
To apply this approach, we need to correlate, based on statistical significance, those households answering having excessive indebtedness with those that do have excessive debt. For this purpose, we use the Pearson χ^2 test of equation (B).

$$\chi^2 = \sum_i \sum_j \frac{\left(O_{ij} - E_{ij}\right)^2}{E_{ij}} \tag{B}$$

Where $O_{i,j}$ is the number of households with distress "i" and a level of indebtedness "j", and E_{ij} is the expected number of observations assuming there is no correlation. We understand that the higher the Pearson χ^2statistic, the more reliable the possibility of rejecting the hypothesis, thus suggesting the independence between the segmentations of economic distress and those based on the indebtedness indicators. Then the threshold maximizing this statistic is the one generating a more significant correlation with household financial distress.

Figure B presents the results using the Pearson χ^2 test for both the FBTI and DTI. We find that while for the distress measure "Excessive", the thresholds are FBTI = 50% and RDI = 1, for the measure of distress "Excessive or High" the FBTI and DTI, the thresholds are 20% and 0.5. Thus these thresholds are not robust to the different distress measures, nor do they generate a reliable result; despite that, all the thresholds obtained have a significant correlation (statistics greater than 3.84 generate p-values less than 5%).

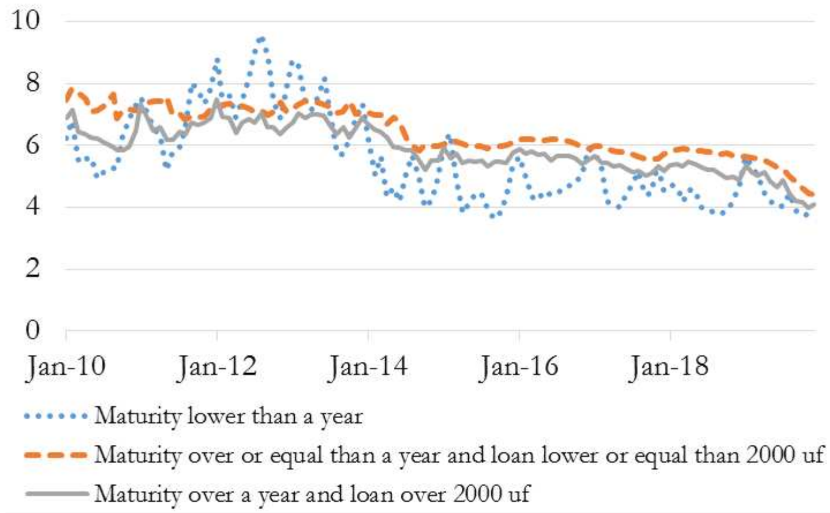
Figure B. Indebtedness and measures of economic distress for all households



Source: Authors' elaboration based on D'Alessio and Iezzi (2013) and HFS2017.
Note: The Y-axis reflects the Pearson χ^2 test statistical level, considering the X-axis's corresponding threshold.

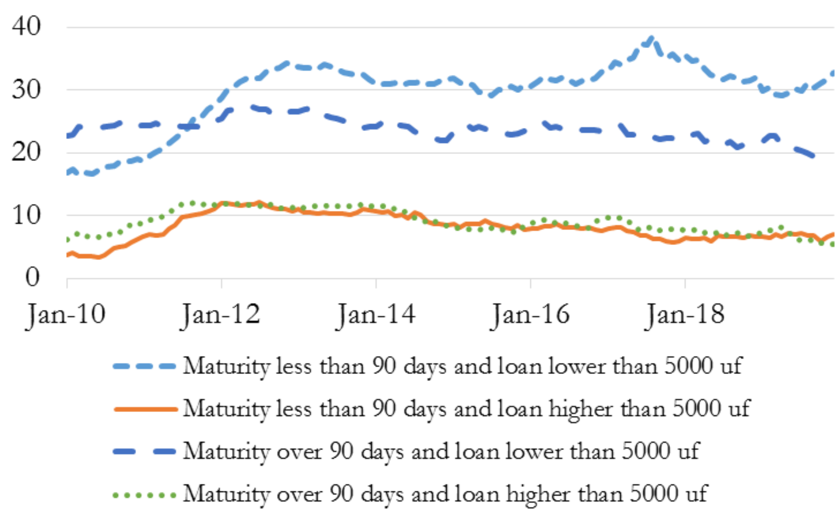
C Interest rate ceilings

Figure C.1. In *unidades de fomento* (UF)
(Percentage)



Source: Authors' elaboration based on historical data sourced from the CMF.

Figure C.2. In nominal Chilean pesos
(Percentage)



Source: Authors' elaboration based on historical data sourced from the CMF.

D Results using the approach proposed

Households income (Chilean pesos)	Households with mortgage loans		Households without mortgage loans	
	FBTI	DTI	FBTI	DTI
100,000	9%	13	n.a	n.a
200,000	19%	26	1%	0.2
300,000	24%	34	6%	1.5
400,000	29%	40	10%	2.4
500,000	32%	45	13%	3.1
600,000	35%	49	15%	3.6
700,000	37%	52	17%	4.1
800,000	39%	54	19%	4.6
900,000	41%	57	20%	4.8
1,000,000	43%	60	22%	5.3
1,100,000	44%	61	23%	5.6
1,200,000	45%	63	24%	5.8
1,300,000	47%	66	25%	6.1
1,400,000	48%	67	26%	6.3
1,500,000	49%	68	27%	6.5
1,600,000	50%	70	28%	6.8
1,700,000	51%	71	29%	7.0
1,800,000	52%	73	30%	7.2
1,900,000	53%	74	30%	7.3
2,000,000	53%	74	31%	7.5

2,100,000	54%	75	32%	7.7
2,200,000	55%	77	32%	7.7
2,300,000	56%	78	33%	8.0
2,400,000	56%	78	33%	8.0
2,500,000	57%	80	34%	8.2
2,600,000	58%	81	35%	8.5
2,700,000	58%	81	35%	8.5
2,800,000	59%	82	36%	8.7
2,900,000	59%	82	36%	8.7
3,000,000	60%	84	37%	8.9
3,100,000	60%	84	37%	9.0
3,200,000	61%	85	37%	9.0
3,300,000	61%	85	38%	9.2
3,400,000	62%	87	38%	9.2
3,500,000	62%	87	39%	9.4
3,600,000	63%	88	39%	9.4
3,700,000	63%	88	39%	9.5
3,800,000	64%	89	40%	9.7
3,900,000	64%	89	40%	9.7
4,000,000	65%	91	41%	9.9

Source: Authors' elaboration.
Note: For an income of 100,000 pesos, no FBTI allows generating an implicit lending interest rate plus spread lower than the interest rate ceiling. So, it was not possible to find a DTI neither.