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Determinants of debt portfolio diversification in Mexican households

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Abstract

This research examines the determinants of debt management in Mexican households defined by the degree of diversification of their debt portfolio. We identify and correct the potential sample selection problem related to credit access using a Heckit approach. Evidence suggests that variables such as income, wealth, and the financial burden of the household, as well as the age, education, and employment situation of the head of the family, significantly impact whether a household concentrates or diversifies its debt. The main limitation is that the data used is only available for 2019, so it is impossible to perform temporal analysis. The originality of this work lies in constructing a debt concentration index as a proxy of debt management, which weights each credit instrument contracted by a household as a ratio of its total debt. We conclude that understanding Mexican families' credit dynamics can contribute to effectively applying public policies that improve their well-being.
JEL Classification: G5, G51, D14, C58.
Keywords: household debt portfolios, credit access, debt concentration, Mexico.

Determinantes de la diversificación del portafolio de deuda de los hogares mexicanos

Resumen

Este trabajo examina los determinantes de la administración de la deuda de los hogares mexicanos definida por la diversificación de su portafolio de deuda. Distinguiendo el potencial problema de selección muestral relacionado al acceso al crédito, se propone la utilización del modelo de Heckman, con el objetivo de identificar y corregir la selectividad y obtener estimadores insesgados. Las estimaciones sugieren que variables como el ingreso, la riqueza, la carga financiera del hogar, así como la edad, la educación y la situación de empleo del jefe de familia, impactan de manera significativa en el hecho de que un hogar concentre o diversifique su deuda. Como principal limitación se tiene que los datos utilizados están disponibles solamente para el año 2019, por lo que es imposible realizar un análisis temporal. La originalidad de este trabajo radica en la construcción de un índice de concentración de deuda como proxi de la administración de la deuda, el cual pondera cada instrumento crediticio contratado por un hogar como una proporción de su deuda total. Se concluye que entender la dinámica de utilización del crédito de las familias mexicanas puede contribuir a una efectiva aplicación de políticas públicas que mejoren su bienestar.
Clasificación JEL: G5, G51, D14, C58.
Palabras clave: Portafolio de deuda de los hogares, acceso al crédito, concentración de la deuda, México.

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1. Introduction

Debt is one essential source of liquidity by which an economic agent obtains funds for diverse purposes related to consumption, investment, and temporary insurance. When we think of analyzing debt, the first that comes to mind is a company requesting a loan or issuing a bond in the market to carry out ordinary operations. However, households also participate in the demand for financial services and use debt for investment but can go beyond by considering also human capital investment and immediate contingencies insurance, for instance.

Samphantharak and Townsend (2009) developed an exciting approach to household finance. They state that households and firms are similar in the way they operate. Studying their finances allows us the construction of financial statements and provides tools to investigate the members' behavior of households associated with specific socio-demographic and economic-financial characteristics.

Analyzing the household as a company admits to adapting existing theories of corporate finance to this type of agent. It also allows us to understand how they manage their assets and liabilities. An example is the possibility of analyzing household indebtedness and asset concentration, applying simple probabilistic models but also complex ones such as neural networks and Bayesian models (Gutiérrez, Capera and Estrada, 2011; Díaz, Sosa and Cabello, 2019; Eichhorn, 2020; Dávila, Ortiz and Cabrera, 2021).

Analyzing this previous literature, we realized there are still many unresolved questions about household finances and how they distribute their wealth to satisfy their consumption through indebtedness. Most of the papers analyze the level of total debt or their access (Martínez, Montoya and Tolentino 2023; Vega, Moreno and Fafán, 2024). However, within the total liabilities contracted by households, obligations can be separated depending on the type of debt instrument. Thus, some households may have departmental and bank credit cards, mortgage debt, payroll loans, and other instruments. If a household contracts more than one type of debt, we can say that it has a diversified debt portfolio; on the contrary, if it has only one type of debt contracted, the debt portfolio is concentrated. So, we can define household debt diversification as the distribution of debt among different types of loans or credit instruments.

Studying the concentration of household debt has significant implications since we can introduce relevant concepts such as risk management and financial education. In this case, more diversified debt portfolios reduce the risk of default (Dynkin, Hyman, and Konstantinovsky, 2002). However, diversification can be extremely difficult without adequate financial education, so from this perspective, households will prefer to concentrate their debt on a single creditor to achieve efficient portfolio management. Following the corporate finance theory related to this topic, Gilson, John, and Lang (1990) show that firms can negotiate their debt portfolio better using fewer debt instruments, which can also apply to households.

On the other hand, diversifying the liabilities contracted contributes to the household's financial stability. In this way, more balanced and manageable debt portfolios can be created, better facing any eventuality that may arise from any unexpected macroeconomic or personal situation. Considering this, households can reduce financial stress. In addition, when portfolios are highly concentrated, avoiding borrowing costs associated with interest rates charged by financial institutions becomes more complex. Diversification makes it possible to optimize these costs by taking advantage of lower rates. In other words, when the liability portfolio is more dispersed, it is easier to have access to credit, contributing to obtaining a better score and credit history with financial institutions. Diversifying household debt can help structure debt payments and establish long-term financial goals.

The motivation for this study arises from the interest in exploring what happens when households have a concentrated or diversified level of debt. In other words, we want to know if it is suitable for a household to contract one or several debt instruments to satisfy its consumption level. The existing literature analyzes indebtedness in an aggregate way (total household debt) without considering the implications that these liabilities come from different sources. Therefore, there is no research for Mexico where household debt is analyzed, considering its concentration or diversification level.

Analyzing the total debt level held by each household gives us a general idea of the constrained expense level they face. However, studying its concentration can help us better understand household preferences regarding the liabilities they use the most, depending on several factors, such as income. This component is usually highly correlated with credit access and a household's level of indebtedness (Alfaro and Gallardo, 2012).

Additionally, we are interested in understanding which factors affect a household's decision to contract one or more debt instruments instead of which specifically they use. In this sense, the proposed variable gives us a general idea of what we want to study. First, proportions allows us to normalize the allocation of debt regardless of the size of debt, permitting us to compare debt management across different income strata. Also, through using proportions we can identify if a household uses more than one debt instrument, and so we can distribute debt and weight it by instrument, depending on its relevance to the total amount of debt. If we use allocations or the number of debt instruments as a dichotomous or categorical variable, we need to discuss probabilistic models, which differ from our goal in this paper.

Therefore, the research problems try to answer the following questions: How do the economic-financial and socio-demographic characteristics of households in Mexico determine debt holdings and the diversification degree of the instruments to which they have access? How important are income, leverage, and financial burden over debt diversification? Thus, we try to test the hypothesis related to how household debt holding and diversification are susceptible to its economic and socio-demographic situation.

The main contribution of this work is to test the existing theories on the determinants of household indebtedness but with a different perspective. The target variable is a debt concentration index constructed from a household's debt instruments as a proportion of its total debt. The purpose of this variable is to give us a measure of household debt dispersion to understand the capacity they have to manage their liabilities when they contract more than one debt instrument or if, on the contrary, they face difficulties managing several credits. Also, this work is a pioneer in this line of research because there is no literature related to household debt portfolio diversification, only about companies' debt and assets portfolio diversification.

To answer the research question and test the hypothesis, the Heckman self-selection model is applied to detect and correct the potential bias associated with access to the debt market. On the other hand, the most relevant results from the estimations confirm the initial hypothesis, considering that households' economic-financial and socio-demographic aspects significantly impact holding debt and diversification. Controlling by self-selection bias in holding debt, we found that variables such as the level of income and debt and the financial burden of households are positively related to the diversification of their obligations. That is, they use several debt instruments to cover their consumption levels. On the other hand, households whose head inhabitant have a certain level of education compared to households whose head inhabitant is not educated tend to build less concentrated debt profiles. The head of household age also positively impacts diversification, with people between 35 and 44 years old being those who disperse their debt levels more than younger people. In addition, household size is also relevant in explaining the dependent variable, where households with more than six inhabitants tend to diversify their debt more than households in which only one person lives. Finally, if the family head is male, the household debt portfolio tends to be less concentrated.

Considering the importance of households understanding the debt market better and using the instruments it offers efficiently, it is essential to clarify that this research does not seek to establish an optimal debt level for Mexican households. However, given a holding level of debt, the study focuses on finding the factors that directly impact whether a household diversifies or concentrates its debt portfolio, considering the different instruments they use.

Given that this work is innovative in the investigation line it follows, although this can significantly contribute to the literature, it can also be a limitation. In this sense, not much empirical evidence helps us corroborate our results consistently, so we must rely on alternative theories and adapt them to our research. Another limitation of this study is that the data we use is cross-sectional for 2019, so we cannot follow households' temporal behavior in managing their debt portfolios.

This research also presents opportunity areas. First, it is interesting to analyze what happened to households' debt structures during the COVID-19 pandemic, whether they changed or maintained the same behavior. Second, this paper serves as a starting point to study the impact of management and debt portfolio administration in public policies on financial inclusion.

The rest of this work is structured as follows: Section 2 presents the state of art. Section 3 explains the methodology, analyzes the data, and describes the variables and the empirical strategy. Section 4 reports the results and discuss them; and finally, section 5 concludes the paper and make some recommendations and final considerations.

2. State of the art

Regarding the literature on household financial statements, several works describe their behavior, but they analyze tenure, allocation, and diversification from the asset perspective. The factors often used to explain these dependent variables may coincide with those that describe the same phenomena but from the standpoint of liabilities. Some investigations on this subject are those of Polkovnichenko (2003), Campbell (2006), Von Gaudecker (2015), and Liu, Li, and Zhang (2022), among others.

However, there is not much-related literature about the concentration analysis of household debt, so this work will be considered an exploratory analysis and a first approach to the subject, especially for Mexico. In this sense, we consider the literature review that gives us an idea of what variables are related to household indebtedness but not the sign it reflects. This investigation does not explain the level of debt as most articles do, so the sign reported by the literature might have a different interpretation of the phenomenon we are trying to analyze.

Considering those above, Rodríguez, Castro, and Meneses (2020) analyze household debt and its financial burden for Mexico, using data from ENIGH[2] 2014. In this work, they used variables such as income and financial burden. Using descriptive analysis, they found that households in the first three deciles are unsustainable and cannot face their obligations. On the other hand, households between deciles four and six are at financial risk.

Dávila, Ortiz, and Cabrera (2021) used a Bayesian model to study household finances. They attempt to measure the prevalence probability of financial stability in Mexican households and use variables such as the source of income, education, savings capacity, financial inclusion, and household socioeconomic level, among others. These authors find that the most important variables that explain the financial stability of households in Mexico are the prudent management of the contracted credit and the conformation of households, underlining the importance of promoting educational initiatives at different levels, modalities, and educational subsystems.

Díaz, Sosa, and Cabello (2019) analyze the determinants of household indebtedness in Mexico through a neural network model. They use data from ENIGH 2016, from which they take or construct variables such as the age of the family head, gender, educational level, socioeconomic stratum, number of economic dependents, and credit card payments. The dependent variable is the household level of indebtedness. They find that the most relevant variable to explain household indebtedness is the possession of a credit card.

Additionally, through a data panel, Eichhorn (2020) studied the factors that explain the over-indebtedness of Chilean households for the years 2014-2017. Using a logit model, this author finds that the income and occupation status of the household head reduces the probability of over-indebtedness. Otherwise, the presence of unexpected expenses affects it positively. Plus, using a cross-sectional approach, she finds that households headed by women and heads of households under 35 years are more vulnerable to over-indebtedness. Also, consumer debt is riskier for over-indebtedness than educational and mortgage debts, which is even higher in the case of the household head belonging to the youngest group.

A European study in the United Kingdom by Tudela and Young (2005) similarly investigates the characteristics that influence household debt. They use a model of overlapping generations to measure aggregate household debt and independent variables such as net financial assets, interest rate, household consumption, and consumer age. The work shows that different future paths for real interest rates could lead to a higher or lower debt-to-income ratio. In neither case, however, recent debt levels appear unaffordable for the average individual inhabiting a household.

Many other authors have analyzed the factors that impact household debt, finding similar results through different estimation methods. These works show that socio-demographic, economic, and emotional characteristics significantly influence the tenure of household liabilities. Among these authors are Costa and Farinha (2012), Zinman (2015), Rahman, Azma, Masud, and Ismail (2020), and Piovarči (2021).

[2] National Survey of Household Income and Expenditure published by the National Institute of Geography and Statistics of Mexico (INEGI, by its acronym in Spanish).

In addition, we use economic competition theories to build the debt concentration index. In this sense, the Herfindalh-Hirschman index measures how concentrated a market or industry is with repercussions in competitiveness, and we adapt it to explain the household debt concentration. Thus, several authors have analyzed this index, including Rhoades (1993), Djolov (2013), and Brezina, Pekár, Čičková, and Reiff (2016).

3. Methodology

3.1 Information sources and database.

To develop this research, we used the National Survey on Household Finances in Mexico (ENFIH, by its Spanish acronym), published in the National Institute of Geography and Statistics (INEGI, by its Spanish acronym). The survey is only available for 2019 and has national-locality geographic coverage. The sample design consists of 17,766 households. We must use an expansion factor to adjust the variance for sample size and represent all households in the Mexican state.

3.2 Dependent variable: concentration debt index.

We use corporate finance and market competition theories to define the dependent variable. No relevant literature has used this same variable from a household perspective.
To create this variable, we define the household debt concentration index, considering each debt instrument households have contracted. The ENFIH describes the following: mortgage credit, credit card, departmental credit card, payroll credit, personal credit, automotive credit, and other credits. Table 1 explains each instrument in detail.

Table 1. Credit instrument descriptions by ENFIH 2019.

Credit Instrument	Descripcion
Mortgage credit	They are long-term loans (5 to 30 years) granted by banks, public institutions (INFONAVIT, FOVISSSTE), or other financial institutions intended for the construction, purchase, expansion, or remodeling of real estate (house, apartment, or land). This credit corresponds to the sum of mortgage loans for primary housing (where the household lives) and secondary housing (any other property different from the primary residence).
Bank credit card	It is a financial product issued by a bank or financial institution that serves as a means of payment in some establishments, but the owner must settle the amount spent on established dates.
Departmental credit card	A financial product that operates under the same concept as a bank credit card, but the grantor or creditor is a commercial establishment whose use is exclusive to that establishment and its branches.
Payroll credit	It is a simple credit of a fixed amount that an employee who receives his salary regularly can obtain through a deposit to his payroll account, where the guarantee

	is his salary. The term can be 3 to 60 months with an automatic charge to the payroll account.
Personal credit	It is a credit of a fixed amount granted to a natural person. It sometimes requires a guarantee, collateral, or promissory note, whose payment term can be established from 3 to 60 months, and payments can be weekly, biweekly, or monthly.
Automotive credit	These are loans through which banks or agencies grant customers money to purchase cars and trucks with financing periods ranging from 6 to 60 months, where the property title remains as collateral.
Other credits	Includes other types of credits such as: Educational loans: Loans to finance university enrollment, master's degrees, stays abroad, or doctorates. Their interest rates are generally lower than those of personal loans. Group loans: Loans that some banks or microfinance institutions grant to groups of 3 or 6 people, some up to 20. The members know each other previously, are organized voluntarily and have a group manager. The main guarantee is that they guarantee each other jointly and indivisibly. Informal credits: These are loans made between individuals or between them and pawnbrokers. They are not financial institutions but service providers that lend money in exchange for leaving a property as collateral or having a joint guarantee.

Source: Author's elaboration with ENFIH 2019 information.

Once we disaggregate the total household obligations by type of instrument, each instrument's proportion over the total household debt is squared. Then, we sum all the values obtained. Namely:

$$DCI = \sum_{i=1}^{6} (s_i)^2$$

Where $\boldsymbol{s_i}$ is the proportion of each instrument over the total debt, and it can be expressed as:

$$s_i = \frac{d_i}{DT}$$

Being $\boldsymbol{d_i}$ the debt instrument under analysis and $\boldsymbol{TD}$ the household total debt. Additionally, if the DCI is close to 0, we can assume that the household debt is diversified. On the contrary, if the index is close to 1, the household debt portfolio is concentrated (Laine, 1995).

Figure 1 shows graphically the distribution of debt concentration for Mexican households. The first approach exhibits that most households in Mexico do not contract more than one debt instrument to satisfy their consumption needs, so Mexican households tend to have a concentrated debt portfolio.

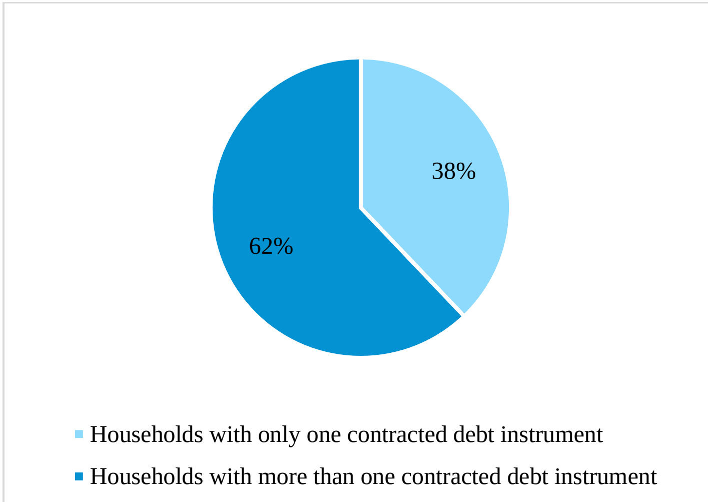

Figure 1. Debt concentration of households in México.
Source: Author's elaboration with ENFIH 2019 database.

3.3 Independent variables: economic-financial and socio-demographic factors.

Considering the literature that analyzes household indebtedness and credit diversification in the business sector, we can establish certain analogies that allow us to identify financial and socio-demographic characteristics to explain our dependent variable. In this work, we only consider the variables defined by these theories since our dependent variable refers to household debt. The sign that we find goes beyond determining whether the level of debt increases or decreases, given that our goal is to analyze the debt concentration and not the household aggregate debt. Table 2 shows the construction and definition of each independent variable involved in this research.

Table 2. Variable description

Variable	Indicator	Description	References
Total Income	$\ln(total\ income)$	The natural logarithm of the total household income, including labor and non-labor income. The total household income includes labor income, financial investments, rental of real estate, and other non-labor income sources such as government support programs, retirement or pensión, transfers from relatives or friends living within the country or outside the country, rental of any property (other than real estate), sale or pawn of goods, profits or earnings from the business, scholarships, and other incomes.	ENFIH 2019 Eichhorn, 2020

Wealth	$\ln(total\ wealth)$	The natural logarithm of the difference between the value of total household assets and the value of total household liabilities.	ENFIH 2019 Gutiérrez, Capera and Estrada, 2011
Education	0. No education. 1. Basic education. 2. Upper secondary education. 3. Bachelor's or equivalent. 4. Post-grad.	A categorical variable that defines the educational level of the household head.	ENFIH 2019 Dávila, Ortiz and Cabrera, 2021
Age	1. Less than 35 years old 2. 35 a 44 years old 3. 45 a 54 years old 4. 55 a 64 years old 5. 65 a 74 years old 6. 75 years old and more	A categorical variable that defines the age group to which the household head belongs.	ENFIH 2019 Díaz, Sosa and Cabello, 2019
Gender	0. Female 1. Male	A dichotomous variable that defines the gender of the household head.	ENFIH 2019 Gutiérrez, Capera and Estrada, 2011
Household Size	1. One inhabitant 2. Two inhabitants 3. Three inhabitants 4. Four inhabitants 5. Five inhabitants 6. Six inhabitants or more	A categorical variable that defines the household number of inhabitants.	ENFIH 2019 Eichhorn, 2020
Employment	0. No empleado 1. Empleado	A dichotomous variable that defines whether the household head is employed or not.	ENFIH 2019 Gutiérrez, Capera and Estrada, 2011

Source: Author's elaboration using bibliographic references.

3.4 Descriptive statistics.

To understand the database, we show some descriptive statistics related to the variables in our models. We employ ten variables: five continuous, three categorical, and two dichotomous.

The debt concentration index shows an average value of 0.88, calculated on approximately 19.5 million households, meaning that most Mexican household debt concentrates debt since its value is close to 1. In addition, its minimum value is 0.23, and its maximum is 1, implying that some households only use one debt instrument. Otherwise, the average income of Mexican households is

97,520.74 pesos. Some households have no income, and others receive more than 7.5 million Mexican pesos. Another variable that impacts the household economy is wealth. It has an average of 758,493.50 pesos with a negative minimum and a maximum of 909 million. The fact that a household has negative wealth implies that its total liabilities are higher than its total assets, which is an unfavorable indicator for the household.

Analyzing the dichotomous variables, we find that 75% of household heads are employed, and 68% are males. Additionally, the categorical variables related to age, education, and household size show that, on average, 22% of the households have a head of the family between 45 and 54 years old. In 57% of the cases, the head of the family has basic education. Finally, predominant households are those with four inhabitants. To understand the descriptive statistics in detail, refer to Table 3.

We also show in the appendix other descriptive analyses by income and wealth percentiles and an example of how we calculate the DCI with actual data for two different households.

Table 3. Descriptive statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
DCI	19,528,410	0.8821	0.1871	0.2395	1.0000
Total Income	36,644,680	98,638.89	327,909.80	0	7,595,000.00
Wealth	36,644,680	757,719.10	5,690,400.00	-12,100,000.00	909,000,000.00
Sex of Household Head:					
Female	11,391,336	0.3109	0.4628	0	1
Male	25,253,344	0.6891	0.4628	0	1
Age of Household Head:					
< 35 years old	6,649,956	0.1818	0.3857	0	1
35 – 44 years old	7,805,986	0.2134	0.4097	0	1
45 – 54 years old	8,134,977	0.2224	0.4158	0	1
55 – 64 years old	6,783,928	0.1854	0.3887	0	1
65 – 74 years old	4,447,118	0.1216	0.3268	0	1
≥ 75 years old	2,761,400	0.0755	0.2642	0	1
Education of Household Head:					
Without education	2,382,174	0.0651	0.2468	0	1
Basic education	20,901,553	0.5716	0.4948	0	1
Upper secondary education	6,245,703	0.1708	0.3763	0	1
Bachelor's education and equivalent	6,310,900	0.1726	0.3779	0	1
Postgrad	725,797	0.0198	0.1395	0	1
Household Size:					
One inhabitant	5,201,181	0.1419	0.3490	0	1
Two inhabitants	7,220,746	0.1970	0.3978	0	1
Three inhabitants	7,318,870	0.1997	0.3998	0	1
Four inhabitants	7,963,215	0.2173	0.4124	0	1
Five inhabitants	5,022,586	0.1371	0.3439	0	1
Six inhabitants or more	3,918,079	0.1069	0.3090	0	1

Labor Status:					
Unemployed	8,852,475	0.2416	0.4280	0	1
Employed	27,792,205	0.7584	0.4280	0	1

Source: Author's elaboration with ENFIH 2019 database.

3.5 Empirical strategy

To study the determinants of the DCI, we use four models that help us to understand better what we are trying to explain. In two models, we analyze the direct effects of socioeconomic factors on the dependent variable. In the remaining two, we include interactions between some independent variables. Given the complexity associated with the relationship between the variables used to explain a specific model, we use the interactions between gender and household income level and the educational level of the head of household and household income. From this perspective, we can explore how differences in perceived household income, considering whether the head is male or female and the level of education achieved by the household's head, affect whether a household takes out one or more credit instruments.

First, we use two regression models using Ordinary Least Squares (OLS) estimation strategy. The first considers only the direct effects, and the second includes the interactions mentioned in the previous paragraph. For this purpose, equation (1), specified below, reflects the OLS model in a generalized form, which can be applied in both using only direct effects and also including the interactions of other variables. In this case, X´s might represent variables or interactions of variables to be analyzed in the estimation.

$$DCI_i = \beta_0 + \beta_1 X_{1i} + \beta_2 X_{2i} + \cdots + \beta_k X_{ki} + \varepsilon_i \qquad (1)$$

$$\varepsilon_i \sim N(0, \sigma_\varepsilon^2)$$

It is essential to mention that the linear regression model using the OLS estimation is just the first approach to understanding the effect of the independent factors on the DCI since the nature of the dependent variable is sequential complex, and it requires more sophisticated models for its analysis. However, the OLS helps us to find if there is any relationship between the household's socioeconomic variables and the concentration of its debt.

In this sense, we propose using a Heckman two-step procedure for identifying and controlling the potential selectivity of access to the credit market. Following the same path, we estimate a Heckman model with only direct effects and also with interactions.

In the first stage, we analyze the determinants of debt access: the probability of a household having any credit, where D_i defines a dummy variable with the access to the debt market, D_{1i}^* is a latent variable determining the switch toward having or not credit, Z_i is a set of socioeconomic determinants of access to debt and u_i is the unobserved component of debt access, which we assume, as usual, distributes as a standardized Gaussian variable with zero mean and finite variance.

Additionally, let us define DCI_i as the debt concentration index for a household i, plus, we assume that access to debt and debt management (as defined by DCI) are potentially correlated and induce selectivity in the portfolio management decision. X_i defines a vector of covariates determining the debt management of the household (also including interactions between variables), and $\lambda(.)$ measures the Mills ratio related to the selectivity of the household when accessing the debt market. Finally, e_i refers to the unobserved component of the debt concentration index, which is assumed to be normally distributed.

In that case, we have that the correct empirical specification of the model must be:

$$D_{1i}^{*} = \gamma_{11}Z_{11} + \cdots + \gamma_{1k}Z_{1i} + u_{1i} \tag{2}$$

$$u_{1i} \sim N(0, \sigma_{\varepsilon_{1i}}^{2})$$

$$DCI_{2i}^{*} = \beta_{21}X_{2i} + \cdots + \beta_{2k}X_{2i} + \phi\lambda(Z_i) + e_{2i} \tag{3}$$

$$e_{2i} \sim N(0, \sigma_{\varepsilon_{2i}}^{2})$$

where,

$$\begin{cases} D_{1i} = D_{1i}^{*} & si \;\; DCI_{2i}^{*} > 0 \\ D_{1i} = 0 & si \;\; DCI_{2i}^{*} \leq 0 \end{cases}$$

4. Results and discussion

The results of this work are presented in two sections. First, we comment on the findings after performing the econometric analysis we explained in the methodology, and later, we discuss these results considering the implications in public policy.

4.1 Econometric analysis

We tested four different models, as shown in Table 4. The first two models use a regression analysis using the Ordinary Least Squares (OLS) estimation methodology. The last two models estimate using the Heckman methodology to control and correct for sample selection bias (Heckit). The results show the expected signs concerning the existing literature. However, in the case of the Heckit models, the employment and wealth variables were excluded from the outcome equation since they identify whether a household holds debt and not so much as whether a household takes out one or more debt instruments.

Analyzing model (1), we observe that the variables related to the household's head socio-demographic characteristics and the reported income level are significant and consistent with the literature. However, it has a very low R-squared of 4.39%. In this sense, we can assume that this model does not adequately and jointly explain the dependent variable. Likewise, model (2), which includes interactions between some of the factors, aiming to improve the predictions made and capture differentiated effects between different groups, also does not have an adequate predictive capacity (R^2=4.55%). Something we can rescue from this model is that there is a differentiated effect by gender and educational level of the household's head concerning the management of the credit instruments contracted by the household.

Models (1) and (2) are the first approach to answer the hypothesis to be tested in this work. For this reason, considering the low predictive capacity of these econometric models, it becomes relevant to find another methodology that fits the characteristics of the data.

From this perspective, if we analyze the nature of the dependent variable, we can recognize a potential self-selection problem in the sample. This variable shows unreported values, which may be associated with the household members hiding information about their debt level and the credit instruments they have contracted. In this sense, individuals may self-select into a group. The sample loses representativeness, as it no longer complies with the principle of randomness. Therefore, the methodology used to identify and solve this problem is a two-stage Heckman model with sample selection correction.

Models (3) and (4) show the estimates using the latter methodology. As a first result of the model (3), it is observed that all independent factors show a negative sign and are significantly related to the debt concentration index. This result implies that, on average, if any of these variables increases, ceteris paribus, the household is more likely to diversify its debt by contracting more credit instruments in the market or distributing the debt in those it has contracted (assuming it has more than one). Another relevant result is the significance of the inverse of Mills' ratio. This significance leads us to confirm the existence of self-selection in the data and that the specification of the Heckman sample selection model is adequate.

Analyzing the independent factors individually in the previous estimations, we observe that if the head of household is male, this favors the diversification of debt concerning female heads of household, presenting a significant effect on the decrease in the concentration of 0.5%.

Likewise, it was found that the household debt portfolio tends to be less concentrated as household heads become older. That is, concerning household heads younger than 35, the increase in diversification is in the order of 1.33, 3.68, 3.37, 2.68, and 0.24 percent for the age ranges 35-44, 45-54, 55-64, 65-75, and older than 75, respectively.

The variation in household debt concentration is highly related to the educational level of the head of household, showing that the higher the education, the less concentrated the household's portfolio of liabilities tends to be. Related to non-educated household heads, the concentration of the debt portfolio decreases by 1.63, 3.16, 4.31, and 6.37 percent for household heads with basic education, secondary education, higher education, and postgraduate education, respectively.

Regarding household size, the increase in the number of people significantly impacts debt concentration. For households with only one inhabitant, adding one member decreases the concentration by 1.07, 3.01, 3.81, 4.64, and 6.58 percent for households with two, three, four, five, and six inhabitants or more, respectively.

Additionally, related to income, we found that, as income increases, the concentration of household debt decreases, implying that households with greater purchasing power have more debt instruments in their portfolio.

Model (4) shows the Heckit methodology with interactions in another attempt to improve the model's robustness and better understand the behavior of debt concentration between groups. Under this understanding, it can be observed that the coefficients previously estimated in the model (3), which showed only the direct effects, keep the same sign. However, they mainly change their value. This change might be related to the interactions, as they pick up part of the effect previously only shown in the direct effect, distributing it among the groups under analysis.

Concerning the head of household sex, we find that households with male heads decrease the concentration of debt by 7.53% compared to households with female heads. Considering the interaction between household income and the sex of the head of household, we show that the effect of income on debt concentration is differentiated depending on whether the head of household is male or female, with a significant difference of 0.77%.

The effects of the age of the household's head on the concentration of household debt also change slightly. Under this perspective and concerning the youngest (under 35 years old), belonging to the age group between 35-44 years, 45-54 years, 55-64 years, 65-74 years, and 75 years and older, decreases the debt concentration by 1.41, 3.72, 3.46, 2.67 and 0.15 percent, respectively.

Regarding the head of household education, the coefficients' values also vary compared with the model (3). Heads of household with primary, secondary, high school, college, or graduate degrees decrease the concentration of household debt by 5.63, 9.19, 7.52, and 13.2 percent, respectively, compared to uneducated heads of household. On the other hand, if we analyze the interaction of this variable with household income, we find again that income has a differentiated effect on the concentration of household debt, considering the educational level of the household head. In this regard, we find that the effect of income on concentration is higher the more educated the head of household is, so if the head of household has postgraduate studies, increases in household income decrease the concentration of debt by 0.71%; this being the highest value among all educational levels.

Finally, the direct effect of household income on its debt concentration is about 2%, implying that if income increases, the debt concentration decreases.

Table 4. Determinants of debt concentration index (DCI).

Variable	OLS (1)		OLS with interactions (2)		Heckit (3)		Heckit with interactions (4)	
Sex (1=Male)	-0.0039	[****]	-0.0813	[****]	-0.0050	[****]	-0.0753	[****]
	(0.0001)		(0.0005)		(0.0001)		(0.0006)	
Total Income (Ln)	-0.0088	[****]	-0.0185	[****]	-0.0095	[****]	-0.0199	[****]
	(0.0000)		(0.0001)		(0.0000)		(0.0001)	
Age (1=< 35 years old)								
35 – 44 years old	-0.0123	[****]	-0.0133	[****]	-0.0133	[****]	-0.0141	[****]
	(0.0001)		(0.0001)		(0.0001)		(0.0001)	
45 – 54 years old	-0.0382	[****]	-0.0388	[****]	-0.0368	[****]	-0.0372	[****]
	(0.0001)		(0.0001)		(0.0001)		(0.0001)	
55 – 64 years old	-0.0336	[****]	-0.0345	[****]	-0.0337	[****]	-0.0346	[****]
	(0.0001)		(0.0001)		(0.0001)		(0.0001)	
65 – 74 years old	-0.0255	[****]	-0.0248	[****]	-0.0268	[****]	-0.0267	[****]
	(0.0002)		(0.0002)		(0.0002)		(0.0002)	
≥ 75 years old	0.0054	[****]	0.0071	[****]	-0.0024	[****]	-0.0015	[****]
	(0.0002)		(0.0002)		(0.0002)		(0.0002)	
Education (1=No education)								
Basic education	-0.0239	[****]	-0.0370	[****]	-0.0163	[****]	-0.0563	[****]

	(0.0002)		(0.0011)		(0.0002)		(0.0013)	
Upper secondary education	-0.0440	[****]	-0.1048	[****]	-0.0316	[****]	-0.0919	[****]
	(0.0002)		(0.0012)		(0.0003)		(0.0014)	
Bachelor and equivalent	-0.0654	[****]	-0.0988	[****]	-0.0431	[****]	-0.0752	[****]
	(0.0002)		(0.0012)		(0.0003)		(0.0014)	
Post-grad	-0.0899	[****]	-0.2237	[****]	-0.0637	[****]	-0.1320	[****]
	(0.0004)		(0.0024)		(0.0004)		(0.0024)	
Household size (1 = One inhabitant)								
Two inhabitants	-0.0211	[****]	-0.0206	[****]	-0.0107	[****]	-0.0100	[****]
	(0.0002)		(0.0002)		(0.0002)		(0.0002)	
Three inhabitants	-0.0502	[****]	-0.0499	[****]	-0.0301	[****]	-0.0295	[****]
	(0.0002)		(0.0002)		(0.0002)		(0.0002)	
Four inhabitants	-0.0609	[****]	-0.0601	[****]	-0.0381	[****]	-0.0373	[****]
	(0.0002)		(0.0002)		(0.0002)		(0.0002)	
Five inhabitants	-0.0686	[****]	-0.0677	[****]	-0.0464	[****]	-0.0454	[****]
	(0.0002)		(0.0002)		(0.0002)		(0.0002)	
≥ Six inhabitants	-0.0919	[****]	-0.0905	[****]	-0.0658	[****]	-0.0647	[****]
	(0.0002)		(0.0002)		(0.0002)		(0.0002)	
Cross-variable terms								
Sex (1 = Male) * Total Income (Ln)			0.0085	[****]			0.0077	[****]
			(0.0001)				(0.0001)	
Post-grad * Total Household Income (Ln)			0.0131	[****]			0.0071	[****]
			(0.0002)				(0.0002)	
Basic education * Total Income (Ln)			0.0015	[****]			0.0045	[****]
			(0.0001)				(0.0001)	
Upper secondary education * Total Income (Ln)			0.0068	[****]			0.0067	[****]
			(0.0001)				(0.0001)	
Bachelor and equivalent * Total Income (Ln)			0.0038	[****]			0.0037	[****]
			(0.0001)				(0.0001)	
Constant	1.0760	[****]	1.1619	[****]	1.0241	[****]	1.1168	[****]
	(0.0003)		(0.0011)		(0.0005)		(0.0013)	
athrho					0.2344	[****]	0.2353	[****]
					(0.0010)		(0.0010)	
lnsigma					-1.6814	[****]	-1.6820	[****]
					(0.0002)		(0.0002)	
Adjusted R-Squared	0.0439		0.0455					
Log-Likelihood					-1.63e+07		-1.63e+07	
Sample size: n (Population sample)	19,303,196		19,303,196		33,835,656		33,835,656	

Notes: The threshold level indicators for statistical significance (p-values) are:
[*] p<0.10 [**] p<0.05 [***] p<0.01 [****] p<0.001.
Source: Author´s elaboration with ENFIH 2019 (INEGI, 2021).

4.2 Discussion of results

The results we found in this research are exciting and original because, although we do not specifically study indebtedness determinants or access as in Vega et.al. (2024), we identify the factors determining Mexican households' debt concentration. From this perspective, our results are consistent with previous household debt level-holding literature. In this sense, socio-demographic factors of the household and economic-financial characteristics explain how households manage their debt instruments.

We use an empirical strategy based on four models to explain the determinants of the debt concentration index with two alternative methodologies. First, we propose an OLS methodology as an exploratory analysis. Second, we use a Heckit methodology to identify and correct the potential sample selection problem in the data. We also include interactions to strengthen estimations.

The first finding is the OLS models with a low R-squared. In this sense, we may assume these models do not correctly explain the dependent variable due to its nature and potential selection bias toward having access to the credit market. This characteristic of the dependent variable leads us to propose the Heckit model to get unbiased and consistent estimations.

From this perspective, the relevant socio-demographic variables in understanding the debt concentration in Mexican households are the sex, age, and educational level of the household's head and household size. In all cases, the relationship is negative. This hypothesis proves that male-headed households diversify their debt more than female-headed households. Otherwise, households where the head has a higher educational level diversify their debt more than those with no education. In this sense, we can use educational level as a proxy for financial education, and this result demonstrates that a higher level of education can facilitate household credit management.

Analyzing income as an economic-financial variable shows that the debt concentration decreases for higher income levels, as it has a negative relationship with the dependent variable. These findings prove that a household with more financial resources can offer solvency, and people will tend to use fewer credit instruments to satisfy their consumption or pay existing debt.

Another relevant aspect is the interaction results. In this sense, we can prove that income strongly influences DCI depending on the household's head sex and education level. These findings explain the different effects between groups. In the first case, the incidence of income over DCI is higher if the head of the household is male, and the same effect appears if the head of the household has post-grad education. From this perspective, interactions can help us better understand how household socioeconomic characteristics are connected, making them contract one or more debt instruments.

It is essential to mention that concentration level also depends on the household's financial goals, and we cannot control or measure it. So, this factor represents a component that could bias our results. In this sense, two households can have the same amount of total debt and pay the same amount every month, but one of them has a DCI equal to 0.25 and the other equal to 0.5. Even though there are similarities between them, the one with the higher DCI is more concentrated, considering debt distribution and the number of debt instruments contracted. Based on this, some households can choose to diversify their debt portfolio to get credit benefits or to use this resource to pay other credit instruments, even if they do not need to use debt to finance their needs. The point is that despite two households having the same characteristics, they can choose different outcomes and DCIs.

On the other hand, considering the impact of public policies on the household economy, this study can help establish regulations in favor of financial inclusion to satisfy household consumption more efficiently. Households where debt are highly concentrated and face a high financial burden are more vulnerable to default due to income shocks compared to those with lower and unconcenttated financial load.

Additionally, our work can contribute to a better distribution of financial resources since it is possible to know what type of financial instruments households demand the most, thus facilitating their access and so the debt portfolio diversification. Also, knowing the management of household liabilities helps to identify the level of financial education that households have or wish to have and thus efficiently manage the risk faced by families associated with the liabilities they contract. Better financial education can contribute to reducing this risk by diversifying its liabilities.

Additionally, it is essential to know that although debt diversification offers benefits, it must be sought out based on careful consideration of our circumstances and financial objectives. Prudent debt management is critical to ensuring the effectiveness and sustainability of debt diversification strategies, including monitoring debt-to-income ratios, affordability, and interest rate risks.

5. Conclusions, recommendations, and final considerations

This work aims to contribute to the existing literature on the analysis of household indebtedness through an alternative approach, creating a concentration measure that allows considering all the debt instruments a household can access. In Mexico, there are few studies on household indebtedness, none regarding the level of debt concentration, and none including all the instruments a household manages, so this research will be a great incentive to continue innovating in studying household behavior.

This work uses a Heckit approach to control the potential sample selection bias under the hypothesis that the people intervening in the debt market are not random. However, they are selected to participate in this market or self-select themselves. For this reason, the results obtained by Heckit are our primary objective since the sample selection bias that presented the data through Mills' inverse was detected and corrected. The rest of the estimations are for exploratory purposes.

Although the results are solid and show a first approach to studies where it considers the different debt instruments a household can access, it is also essential to explore its limitations. Firstly, having cross-sectional data for a single year does not allow us to analyze what happens to the concentration of household debt over time, considering market effects, such as the COVID-19 pandemic that recently ended. Secondly, the lack of literature on the specific subject we want to investigate does not allow for directly contrasting the results obtained. Hence, the adoption of alternative theories was essential to developing this research. However, it is relevant to consider that the effects found are consistent with economic intuition.

Considering the future research agenda, this work is a starting point for implementing more complex studies on households, assuming those can act as companies as Samphantharak and Townsend (2009) propose. First, we recommend replicating this study in other countries to compare the influence of socio-demographic and economic-financial factors under different macroeconomic circumstances. In this context, we can establish patterns in household behavior and how households manage their credit instruments.

A second approach is to analyze the DCI by clusters, such as income or wealth level. This study can give us a better picture of the behavior of the households depending on the group to which they belong, as there are differences between clusters.

A third approach for future research would be to relate debt concentration and vulnerability to income shocks, to analyze the way debt portfolio exposure affects households once we consider access to credit and debt management as a sequential problem with a potential selection bias.

Finally, this work permits understanding another dimension of financial deepening by focusing on the liquidity risk-management dimension of households' debt portfolios in a developing context. Additionally, analyzing household debt concentration helps policymakers identify potential economic risks and vulnerabilities. It provides insights into the distribution of debt across different income groups and sectors, highlighting areas that may require targeted interventions or policy adjustments.

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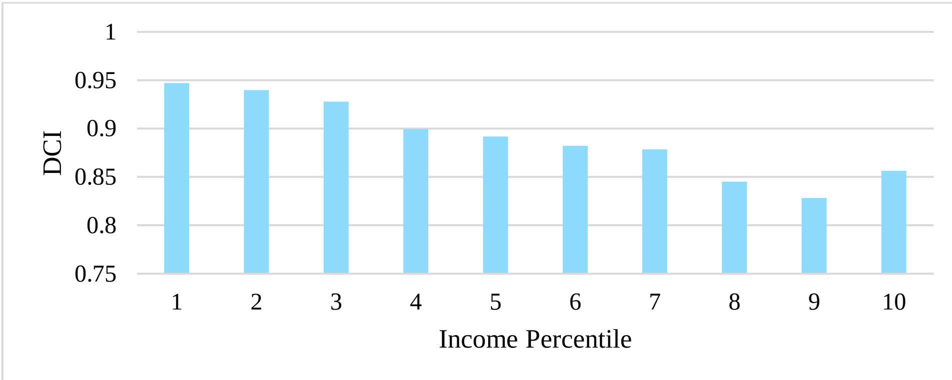
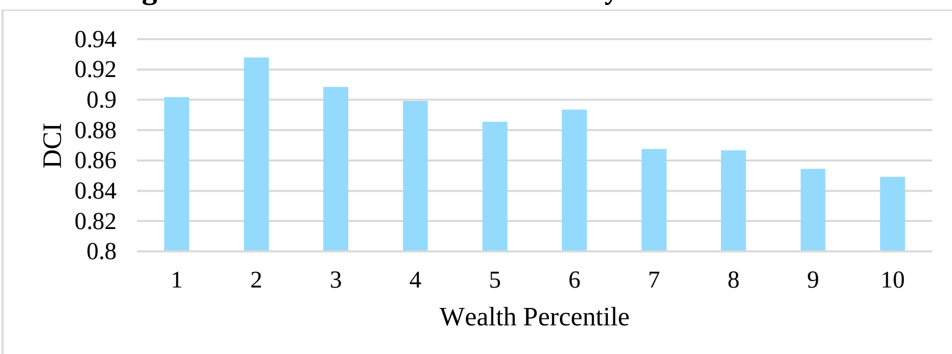
Appendix

Figure A.1 Debt Concentration Index by Income Percentile



Source: Author's elaboration with ENFIH 2019 database.

Figure A.2 Debt Concentration Index by Wealth Percentile



Source: Author's elaboration with ENFIH 2019 database.

Table A.1 Calculation of Debt Concentration Index.

Household	Mortgage Credit (MC)	Credit Card (DCC)	Payroll/Personal Credit	Automotive Credit	Other Credits	**Total Debt**
598	311,198.00	30,000.00	0	162,620.00	22,000.00	**525,818.00**
605	0	0	9,000.00	0	0	**9,000.00**

Household	$S_1 = \left(\frac{MC}{TD}\right)^2$	$S_2 = \left(\frac{DCC}{TD}\right)^2$	$S_3 = \left(\frac{PPC}{TD}\right)^2$	$S_4 = \left(\frac{AC}{TD}\right)^2$	$S_5 = \left(\frac{OC}{TD}\right)^2$	$\boldsymbol{DCI = \sum_{i=1}^{5}(s_i)^2}$
598	0.3502	0.0033	0	0.0956	0.0018	**0.4509**
605	0	0	1	0	0	**1**

Source: Author's elaboration with ENFIH 2019 database.