Journal of Behavioral and Experimental Finance 34 (2022) 100660

Contents lists available at ScienceDirect

Journal of Behavioral and Experimental Finance

journal homepage: www.elsevier.com/locate/jbef

Full length article

The impact of financial literacy on the quality of self-reported financial information

Carlos Madeira [a,1], Paula Margaretic [b,*,1,2]

[a] Central Bank of Chile, Chile
[b] Universidad Adolfo Ibañez, Chile

ARTICLE INFO

Article history:
Received 30 June 2021
Received in revised form 7 April 2022
Accepted 14 April 2022
Available online 4 May 2022

JEL classification:
D14
D18
E21
G21
G50
G53

Keywords:
Credit
Financial literacy
Financial education
Mortgage refinancing
Household finance surveys
Saving behavior
Measurement errors

ABSTRACT

Household finance surveys are now common in many countries. However, the validity of the self-reported financial information is still understudied, especially for complex choices. Using a unique matched dataset between the Chilean Household Finance Survey and the banking system's loan records, we find a positive effect of financial literacy on the accuracy of loan reporting. These findings are robust to the use of several proxies for financial literacy, such as the OECD INFE measure, the knowledge of the respondent's personal pension account type, or the use of electronic means of payments. Using a nearest neighbor matching estimator, we confirm that the effect of financial literacy on the accuracy of loan reporting is causal even after controlling for several observable characteristics.
© 2022 Elsevier B.V. All rights reserved.

1. Introduction

Access to financial services has increased all over the world, both in terms of digital services and in terms of the traditional "bricks and mortar" branches of banks, cooperatives or micro-finance institutions (Demirguc-Kunt et al., 2018). However, financial services require understanding the transfer of different sums of costs and benefits over time. In this respect, financial contracts and services are unlike other transactions in which customers pay for a good or service that starts being enjoyed right away.[3] For this reason, it is essential that borrowers understand correctly the financial products available to them, whether for saving or borrowing, and how these will impact their current and future welfare (Hastings et al., 2013). Financial literacy programs can reduce borrowers' over-indebtedness and loan repayment difficulties (Brown et al., 2016), encouraging a more responsible use of debt and the avoidance of high interest rate products (Klapper et al., 2013). During the Great Financial Crisis, many of the over-indebtedness problems with high interest rate products were associated with less financially educated borrowers (Klapper et al., 2013; Gomes et al., 2021). People with strong financial skills show a better retirement planning, risk diversification across different assets and savings for retirement or precautionary motives (Lusardi and Mitchell, 2011; Behrman et al., 2012). Financial literacy also sharply increases with educational attainment (Lusardi and Mitchell, 2014; Brown et al., 2016).

Abbreviations: SFC, Survey of Financial Capabilities; INFE, International Network on Financial Education; FPC, first principal component; SHF, Chilean Household Finance Survey; AAPOR, American Association for Public Opinion Research; HH, household; resp., respondent; stud., studies; fin., financial; INR, item non-response

* Corresponding author.
E-mail addresses: carlosmadeira2009@u.northwestern.edu (C. Madeira), paula.margaretic@uai.cl (P. Margaretic).

1 Both authors, Carlos Madeira and Paula Margaretic, took a joint role in all the tasks.

2 We would like to thank Agustin Sotelo for excellent research assistance. All errors are our own.

3 Even in the case of durable goods, such as homes or vehicles, their utility starts immediately and the flow of future use happens regularly and in a predictable way.

https://doi.org/10.1016/j.jbef.2022.100660
2214-6350/© 2022 Elsevier B.V. All rights reserved.

In this paper, we investigate the impact of financial literacy on the quality of households' self reported debt information, by comparing the Survey data relative to their administrative bank loan records. The intuition is that Survey respondents with higher financial education are better able to understand the terms of their financial products and, therefore, to provide more accurate information during the Survey interview. In such a case, financial literacy could serve as an instrument for the accuracy of survey reported financial data. Our study takes advantage of a unique matched dataset between the Chilean Household Finance Survey and the Banking Loan administrative records of the Survey respondents. The matched Survey-Administrative loan dataset improves considerably upon previous studies for other countries, because it is a micro dataset of loan reports in both data sources; it is not a comparison between aggregate debt amounts in Survey data and administrative records (Zinman, 2009). To the best of our knowledge, we are one of the few studies that investigate the relationship between the mis-reporting of Survey information and financial literacy (Madeira et al., 2022).

Household finance surveys are increasingly used to study families' decisions on investments, borrowing and financial behavior, especially at the international level where comparable administrative records are often unavailable (Christelis et al., 2013; Bover et al., 2016; Badarinza et al., 2016). This is especially true for questions about financial access and behavior, where often administrative registers are unable to distinguish whether households do not have access or simply do no want the financial products (Karlan and Zinman, 2008; Demirguc-Kunt et al., 2018). However, studies on measurement errors have shown some differences in households' loan reporting between survey and administrative records (Zinman, 2009; Fesseau and Mattonetti, 2013; Brown et al., 2015), which warrants further research about the causes and implications of survey respondents' loan mis-reporting (Karlan and Zinman, 2008).

Our matched Survey-Administrative dataset provides the households' banking loan contracts (including mortgages, consumer installment loans, credit cards and credit lines) and their self-reported cross-sectional information on the household demographic characteristics, income and loans for one Survey year (with household interviews being in 2011, 2014 and 2017). Therefore, we assess at a micro-level how the Survey self-reported loan information differs across respondents and across respondents' financial literacy. This allows us to test whether financial literacy impacts the mis-reporting of the loan(s) in the Survey (extensive margin) or the differences in the loan amounts between the Survey information and the loan records (intensive margin). Furthermore, the mis-reporting of loan amounts at the individual level can be separated between over-reporting and under-reporting (Karlan and Zinman, 2008). To analyze the impact of financial literacy on debt mis-reporting, we use several proxies for financial literacy. To begin with, we rely on the OECD INFE measure of financial education (Atkinson and Messy, 2011; OECD, 2020), with INFE standing for the International Network on Financial Education. In particular, we sum the sub-indexes of Attitude, Knowledge, Behavior and Search from the INFE measure, with these sub-indexes being computed for each respondent in the Chilean Household Finance Survey.[4] As additional proxies for financial literacy, we consider respondents' knowledge of their personal pension account types (Lusardi and Mitchell, 2014) and the use of electronic means of payments (Akin et al., 2012; Fujiki and Tanaka, 2018; Fujiki, 2020b).

We show that the more financially literate respondents provide more accurate Survey loan reports, as compared to the administrative records, even controlling for several characteristics, such as the respondents' education, civil status, gender or household size. Indeed, we find that the respondent's education level becomes insignificant when we rely on the OECD INFE measure of financial education, presumably because the INFE proxy provides a more complete assessment of individuals' financial education. Furthermore, we show that results continue to hold if instead of using one given proxy for financial literacy, we use the first principal component factor (Rencher and Christensen, 2012) of our three proxies of financial literacy together (namely the respondent's knowledge of her personal pension, the use of electronic means of payments and the sub-indexes of Knowledge, Behavior and Search from the INFE measure), coupled with the respondents' completed education level.

Finally, using a nearest neighbor matching estimator, we provide strong evidence for the causal effect of financial literacy on households' loan reporting. To run the exercise, the treated units are the financially literate respondents; the non-treated units are the financially illiterate respondents. To proxy for financial literacy, we consider the financial literacy index that we obtain from the principal component factor model. To identify the financially literate respondents, we rely on two alternative definitions of treated units: (i) those whose first principal component financial literacy score is above the 75th percentile of the empirical distribution of this variable; (ii) those respondents whose first principal component financial literacy score is above the median (results are robust to other thresholds). To identify the group of neighboring respondents for each treated unit, we rely on an exhaustive matrix of control variables, including sex, civil status, region of residence, the number of generations present in the household, the loan type (when corresponding), plus a set of indicators about the timing and place of interview, and the rounding behavior and respondents' participation during the interview. Similarity between respondents is hence based on a weighted function of the covariates for each observation. Results provide strong evidence in favor of the causality impact of financial literacy on Survey loan reporting. Interestingly, when comparing the average treatment effect of financial literacy on households' loan reporting with its corresponding OLS estimate, the average treatment effect is smaller.

Summing up, the goal of our work is close to the studies of Zinman (2009), Brown et al. (2015). However, their studies are limited to the comparison of household aggregates in national accounts and administrative datasets. We improve upon this literature by showing the extent of debt mis-reporting at the level of individual respondents and debt type and by being the first to study how loan mis-reporting is related to financial literacy. This study is also related to a growing literature on how surveys of small firms and households can inform about the financial problems faced by families and entrepreneurs, especially in developing countries (Beck et al., 2015; Beck and Brown, 2015; Cull et al., 2019). Last, our work has strong policy implications for regulators and it is consistent with previous findings in the literature that show that lower education and lower financial literacy are strongly associated with debt risks for the borrowers (Disney and Gathergood, 2013) and for the financial system. A lack of financial literacy in loan markets hinders competition among lenders (Allen et al., 2019), with a negative effect on efficiency and harming poorer minorities (Tufano, 2009; Woodward and Hall, 2012).

This paper is organized as follows. Section 2 reviews the literature on the impact of financial literacy on financial outcomes,

[4] To compute these financial literacy sub-indexes for the INFE measure, we combine the Chilean Household Finance Survey with the Chilean Survey of Financial Capabilities (SFC). The SFC measured in 2016 an extensive set of financial literacy indexes for 1224 Chilean households. Specifically, in this paper, we impute the sub-indexes of Attitude, Knowledge, Behavior and Search for each Household Finance Survey respondent using the mean indexes of similar SFC individuals, with similarity being defined based on age (10 year dummies), gender, education level and household income quintiles.

with a particular focus on empirical studies and the econometric methodologies for identification. Section 3 summarizes the methodology and the data. In particular, regarding the data, it presents the Survey-Administrative matched dataset, the way we proxy financial literacy, the borrowers' characteristics and financial behavior. Section 4 shows the impact of financial literacy on borrowers' loan mis-reporting. Finally, Section 5 concludes with some policy implications.

2. Relation to the literature

Our work is related to two strands of literature. First, this paper is linked to the research that analyzes the quality of self-reported financial information by linking the Survey and the administrative data at an individual level. Within this strand, Maynes (1968) focus on savings and loans; Bhandari et al. (2020) concentrate on business surveys' mis-reporting; Bound and Krueger (1991), Pedace and Bates (2000), Kapteyn and Ypma (2007), Paulus (2015), Alwin et al. (2014) examine earnings; Bound and Krueger (1991) provide a survey on linked data for multiple items; Alvarez et al. (2012) investigate risk preferences, demographics and financial asset management; Ameriks et al. (2015), Neri and Monteduro (2013), Baker et al. (2021) focus on wealth; Eggleston and Reeder (2018) investigate asset income, among others. These studies typically rely on individual identifiers (such as the identity number and the social security number) or survey respondents' characteristics, to link the survey and the administrative records. Among them, Maynes (1968) and Madeira et al. (2022) are, to our knowledge, two of the few previous papers working with debt data.

We contribute to this strand of literature on two grounds. On the one hand, by having access to a novel match between the complete administrative credit records containing recent information for all the people who have ever applied for a banking product in Chile (over the period between January 2003 and December 2018) and the national Survey of Household Finances (waves 2011, 2014 and 2017), which is representative of the national urban population. This is a contribution in itself, as most countries do not have administrative debt data, and even when they have, linking administrative records to surveys for such a long period of time is rarely possible. On the other hand, our paper adds to this literature by examining to what extent households' financial literacy and financial education affect the quality of self-reported debt information. Our main finding is that financially literate households provide more accurate responses about their liabilities relative to financially illiterate households; therefore, financial illiteracy leads to measurement errors in the self-reports. This finding has an important policy implication regarding the interpretation of the treatment effects of financial education programs on self-reported financial behavior. This is because it means that when researchers are interested in the impact of a financial education program on financial behaviors, measurement error will affect their ability to estimate unbiased causal effects. Systematic reporting errors generally bias causal estimates, especially when the source of measurement error (financial illiteracy) is correlated with the treatment of interest (Blattman et al., 2016).

An additional implication of our results is that financial literacy may be correlated to some omitted psychological individuals' traits, which in turn may lead to biased estimates for the impact of financial education on (self-reported) financial behavior. This is because we find that the average treatment effect of financial literacy on households' loan reporting is smaller than its corresponding OLS estimate. Indeed, within the strand of literature emphasizing this correlation (between financial literacy and omitted psychological individuals' traits), Fernandes et al. (2014) find larger effect sizes in studies that estimate the impact of financial literacy on behaviors using OLS regression compared to studies that rely on instrumental variables or experimental designs to account for the endogeneity of financial literacy and for omitted variable bias.

Second, this work is linked to the micro analyses on survey measurement errors. Measurement error happens in household finance and wealth surveys for a variety of reasons, including processing error, memory or recall difficulties, or (un)intentional misunderstating of one's assets or debts (Neri and Monteduro, 2013; Madeira et al., 2022). Memory or recall difficulties may happen more often for assets, debts and net wealth than for wage income. This is because wage is an income that is regularly received (typically, every month), with a similar amount. In contrast, the loan payments and the residual value of the loans change substantially every month (Kennickell, 2017; Madeira et al., 2022). It is also possible that households find their wealth and debts to be more sensitive pieces of information to report than income, hence, preferring to understate their values (Kennickell, 2017). One consequence of people mis-reporting their wealth and debts is that the assessments of policy makers regarding households' financial risks and their implications for the banking system may be biased (Meriküll and Room, 2020).

When investigating measurement error, the literature relies heavily on the assumption that discrepancies between the survey and the administrative records are mainly due to survey errors (Baker et al., 2021; Mittag, 2019; Bound and Krueger, 1991; Eggleston and Reeder, 2018; Zinman, 2009; Brown et al., 2015).[5] We share with this literature its common assumption, as we argue that the quality of the Chilean administrative debt records is high. We add to this literature by proposing a micro assessment of the Survey quality by matching at individual and debt type level the Survey respondents' responses with the administrative records. Our matching allows us to shed some light on the nature of errors and the impact of financial literacy on these different types of errors. Indeed, we show that financial literacy leads to smaller errors in the intensive margin, that is, in the reported loan amounts, conditional on having correctly reported the debt type. Oppositely, being a financial literate household does not imply having a smaller probability of making errors in the extensive margin.

3. Data and methodology

3.1. The Chilean Household Finance Survey

For this study, we use the national waves of the Chilean Household Finance Survey (SHF) in 2011, 2014 and 2017, hereafter the *Survey*. Each sampled household has one member who is selected as the respondent, with this member being the household person with the greatest knowledge of the family finances or with the highest income. The Survey is a cross-sectional, interviewer administered survey. It contains a mix of open-ended and closed-ended questions. The Survey elicits demographic, net wealth, asset, debt and income information for the household or all the household members when corresponding. The sample selection of the Survey was based on an exhaustive list of homes from the Chile Internal Tax Service and is therefore representative of the national urban population after expansion factors are applied to each unit (Banco Central de Chile, 2018).

Due to the absence of a single administrative credit register that includes all the non-banking lenders, the Survey is the only micro data source in Chile with information on household

[5] To our knowledge, only three studies depart from that assumption (Kapteyn and Ypma, 2007; Abowd and Stinson, 2013; Hyslop and Townsend, 2020).

loans from all types of lenders and with extensive details on the characteristics of borrowers. The Survey has detailed measures of income, assets and savings (financial assets, vehicles and real estate assets) and debts, including mortgage, educational, auto, retail and banking consumer loans (namely credit cards, lines of credit and installment loan contracts). In order to cover debts exhaustively, the Survey asks about the loan terms (debt service, loan amount and maturity) for the four largest mortgages (including both the main mortgage and the associated unsecured loans for related expenses, such as contract fees, appraisal or remaining home payments) and for the three main loans of each remaining debt category. The loan categories that we consider in this paper are credit cards and credit lines, installment loans with banks and mortgages. Respondents respond debt questions about the household (in the case of the mortgage loans) or about all household members (in the case of the consumer loans). Table A.1, in Appendix, reports the AAPOR response rate for the three years.

To obtain a more accurate view of households' indebtedness, the Banking Authority linked each Survey response to the administrative records; hereafter, the *Survey-Administrative dataset*. The administrative credit information includes all the people who have ever used a banking product; it is available over the period January 2003 and December 2018. The match between the Survey responses and the administrative records is possible thanks to the Chilean national identity number that Survey respondents are asked to provide. Chileans make regular use of their national ID to obtain discounts in the supermarkets, to apply for loans, or to use the health system; therefore, participating households are usually comfortable with providing their ID information during the Survey interview. Furthermore, each national identity number is followed by a validation digit, which allows us to test whether the stated number is correct. This prevents mismatching in the sense that we can validate that there was no mistake in the recorded identity number during the interview process.

Precisely, the link between the Survey and the administrative records is done at the respondent (thanks to national identity number) and type of credit (mortgages, installment loans, and credit card and credit line loans). Hence, if, for a given respondent, the Survey and/or the administrative records register more than one loan per type of credit, loans are consolidated as if they were one. This way, we sum all the loans in each debt category reported by the respondent in the Survey and then compare it to the sum of all the loans in the same debt categories for the administrative register. Finally, to avoid the influence of disparities between the Survey responses and the administrative records, for the match, we look for the closest administrative record to each Survey response over a time window of two months around the date of the interview. Precisely, let t^S be the date of the Survey interview and t^A, the adjusted administrative record date. Hence, $t^A = t^S + k$, with $k = 0, -1, 1, -2, 2$. The reason for including such a time window is to account for situations where, for instance, a borrower asks for a new loan at the end of a month, say month t_1, but because at the time of the interview, it does not remember the exact date the loan was granted, it reports it in the Survey as a loan at $t^S = t_1 + 1$, whereas the bank registers it at t_1.

There are three remarks to make about the Survey-Administrative matched dataset. First, the universe is limited to individuals who have used a banking product; therefore, it does not include loans from retail stores, unions or other lenders, such as car dealers. Second, the matched data provides information on the original loan amount at the time the contract was made, the total payment made due to that loan in a certain month and whether the loan is in delinquency or not. However, it does not include information on interest rates or other fees and costs charged. Note that the administrative banking loan dataset is not a panel data of loans. It lists all the loans of each individual in a given month, but it is not possible to connect each loan with loans in other periods. Third, we exclude all loans in the administrative records with unusually low loan amounts, that is, lower than 2000 Chilean pesos (around 3 US dollars).

Table 1
Number of total respondents in the Survey and the matched Survey-Admin datasets.

Wave	Survey	Survey with ID	Survey-Admin[1]
2011	4059	2329	933
2014	4502	2362	1132
2017	4549	3356	1790
Total	**13,110**	**8047**	**3855**

Notes: This Table reports, for each Survey wave, the total number of respondents (second column), the number of respondents who provided a correct ID number (third column), and the number of respondents with a correct ID number and positive amounts of debt in the administrative dataset (fourth column). The superscript 1 corresponds to the Survey-Admin matched dataset conditional on the respondent having positive amounts of debt in the administrative dataset.

In this paper, we argue that the quality of the administrative records is high. There are three main reasons for that. First, the administrative data is a loan register that is used for several supervision purposes, such as the interest rate ceiling regulation. Furthermore, banks use it to check the total banking loans of prospective borrowers. Consequently, each bank delivering information would have incentives to report mistakes by the other banking competitors. Moreover, if a bank failed to accurately report a loan, it would be a serious legal violation, implying large fines and reputational losses. Therefore, there are supervisory incentives to keep a clean register, report mistakes and correct the dataset. Second, our analysis focuses on two simple concepts that banks regularly report to the regulator: Debt ownership and total debt amount. Third, while the Banking Authority requires all banks to update their information every month, our dataset is not high-frequency. Therefore, it seems unlikely that possible errors would go unnoticed one year after the last Survey wave (in 2017) when the matching process was made.

Table 1 reports, by Survey wave, the number of households being surveyed (second column of Table 1), the number of respondents having provided a correct national ID number (third column of Table 1), and finally, the number of respondents with a correct ID number and having been matched in the administrative banking loan records, conditional on registering a non-zero loan amount in the administrative records over the period where each Survey wave took place (fourth column).

Table 1 shows that there are 13,110 households in total in the Survey dataset, with 8047 of them having provided a correct national ID number. Furthermore, out of those 8047, there are 3855 observations with positive amounts of debt in the administrative records over the period where each Survey wave took place.[6] Table A.2, in Appendix, shows that the subsample of households

[6] Table 1 also shows that the ID disclosure rate of the Survey respondents has increased over time, reaching a 74% (3356/4549) in the most recent survey wave of 2017. One reason for this pattern could be due to changes in field methods, interviewer training, supervision and survey management from the fieldwork companies. Indeed, the fieldwork company changed from the Social Observatory of University Alberto Hurtado in 2011 to the Ipsos company in 2014 and 2017. Another reason may be due to a learning effect of the respondents: 2011 was the first wave in which the respondents were asked to provide their ID number. This change was implemented by including an additional section with several questions asking information that may be perceived as sensitive (this section was not part of the Survey questionnaire between 2007 and 2010). Summing up, it is reasonable to argue that the Survey companies may have gained experience about how to better elicit this sensitive information over time and that the respondents may have got used to providing this information.

having correctly provided their ID number during the Survey interview is representative of the total Survey sample.

3.2. Proxies for financial literacy

Financial literacy refers to the ability to manage personal finance matters in an efficient manner, which includes the knowledge of making appropriate decisions about personal finance; the understanding of various economic and financial principles and concepts and the ability to use available services and tools (Hung et al., 2020; Zait and Bertea, 2014; Huston). From the three elements of the above definition, we expect that the understanding of various economic and financial principles and concepts would be the most relevant aspect to explain discrepancies between the Survey and the administrative records. This is because respondents without a good understanding of financial concepts like consumer debt, interest payments, types of financial service providers (all else equal), would be more likely to incorrectly report their debt type, the debt provider, the owner of the debt and/or the loan amount. For instance, a respondent without the knowledge of basic financial concepts might mistake a consumer loan from a retail store for a consumer loan from the corresponding retail bank.[7]

To proxy for financial literacy, first, we rely on the information on whether the respondent knows her individual pension account type.[8] Second, we consider a categorical variable for the respondent (or someone in the household) using automatic means of payments, such as automatic bill payments with credit card or current account (Lusardi and Mitchell, 2011; Akin et al., 2012; Fujiki and Tanaka, 2018; Fujiki, 2020a). Note that knowing her capitalization account type may be mainly capturing one dimension of the financial literacy definition given above, that is, the knowledge of the respondent's personal finances. In turn, using automatic means of payments relates to the household's ability to use available services and tools. Both proxies come from the Household Finance Survey. The third proxy for financial literacy that we rely on provides a more general assessment of households' financial literacy. It combines the Household Finance Survey with the Survey of Financial Capabilities or SFC. The SFC measured in 2016 an extensive set of financial literacy indexes for 1224 Chilean households, following the now standard OECD INFE methodology to measure financial literacy (Atkinson and Messy, 2012; OECD, 2020).[9]

The INFE methodology considers four financial literacy indexes, namely the Financial Attitudes, the Financial Behavior, the Financial Knowledge, and the Search Behavior for Financial Information. Precisely, the Financial Attitudes index measures on a scale from 0 to 4 whether households prefer to spend money instead of saving it. In turn, the Financial Behavior index measures on a scale from 0 to 8 a set of financial behaviors, such as, thinking before making a purchase, paying bills on time, budgeting, saving or borrowing to make ends meet. The Financial Knowledge index measures on a scale from 0 to 8 the basic knowledge about a range of financial topics, such as, division, risk–return trade off, inflation, interest rates, and asset diversification. Last, the Search Behavior for Financial Information index measures on a scale from 0 to 2 how much information the household gathers on different financial products and financial institutions and the diversity of information sources on financial products that households rely on (internet, financial advisors, whether in person or by phone, friends, newspapers, among other). Appendix A.1, in Appendix, details the INFE methodology and the four sub-indexes.

In this paper, we impute these financial literacy sub-indexes for each Survey of Household Finance respondent using the mean indexes of similar SFC individuals, with similarity being defined based on age (10-year dummies), gender, education level and household income quintiles.[10] Table A.3, in Appendix, exhibits the mean financial literacy sub-indexes for the sample of households having reported their national ID number in the Household Finance Survey, which is the sample that we consider in this paper. The Table also reports the mean composite index that results from adding the categories Behavior + Knowledge + Search (last column). The Table reports these mean indexes for all the respondents and for respondents being classified by the respondents' income quintile and by education level.

The reason for including the composite index Behavior + Knowledge + Search is that the Attitude category relates to whether the respondent prefers to spend money instead of saving it. In a developing economy like Chile, one could argue that the Attitude index is not strongly related to households with better financial education, but it rather shows a more conservative spending behavior among the least educated and lower income households that might not have access to the debt markets. Supporting the latter, Table A.3 shows that the Attitude category is decreasing in income, in contrast to the other sub-indexes. As a matter of fact, the other three sub-indexes (Behavior, Knowledge and Search) are all increasing in the income and the education of the respondent. For the above reasons, we compute the composite financial literacy index by summing the Behavior, Knowledge and Search sub-indexes. Hereafter, we will refer to this constructed composite financial literacy index as the *INFE financial literacy index*.

To conclude, Table A.4, also in Appendix, examines the link between respondents' education level and our three proxies for financial literacy, namely whether the respondent knows her pension account type (column two), whether the household uses automatic means of payments (column three) and the continuous INFE financial literacy index (which we obtain from the addition of the Behavior, Knowledge and Search sub-indexes, column four). Interestingly, Table A.4 shows that our three proxies for financial literacy are increasing in the respondents' education level. In the next section, we detail how we deal with this possible multicolinearity between education and financial literacy.

[7] There are three companies in Chile that own both a retail store and a bank specialized in consumer credit. These banks and retail stores work as separate institutions for administrative purposes, but are often located in the same commercial branch and under a similar advertising brand name. Therefore, it is possible that some borrowers confuse loans from a bank and a retail store of the same name or, she could incorrectly report a mortgage as a banking loan, when in reality, it comes from a non-bank institution, such as an insurance company.

[8] In Chile, there are five different types of funds that the pension fund administrators can manage, with these funds varying in the riskiness of the assets the administrators can invest on.

[9] The INFE have developed a survey to capture the financial literacy of people from very different backgrounds in a wide range of countries. The questionnaire is designed to be used in face-to-face or telephone interviews. Core questions within this survey cover financial knowledge, behavior and attitudes relating to various aspects of financial literacy including budgeting and money management, short and long term financial plans, and financial product choice. The questionnaire has been used in 14 countries across 4 continents (Atkinson and Messy, 2012).

[10] Although we do not observe the exact financial literacy measure of each respondent, we can identify moments (such as the mean) of its distribution. The literature has applied this strategy of using the moments of an unknown variable as a regressor in the case of financial literacy (Madeira, 2021) and earnings (Cunha et al., 2005). Both papers apply variables measured in other surveys which are not available in the main dataset of the study.

Table 2
Empirical distributions of the proportional differences $y_{i,t,d,A-S}$, distinguishing by debt type (in %) .

Debt Category	P_{10}	P_{25}	P_{50}	P_{75}	Mean
Mortgages	3.45	9.78	29.93	64.66	44.41
Credit card and lines	2.40	10.25	39.14	94.91	59.26
Installment loans	3.17	9.24	32.20	77.88	50.46

Notes: This Table exhibits descriptive statistics of the empirical distributions of the absolute proportional differences $y_{i,t,d,A-S}$ of loan amounts across different debt categories. P_{10}, P_{25}, P_{50}, and P_{75} are the tenth, twenty-fifth, fiftieth, and seventy-fifth percentiles of these empirical distributions, respectively. The Table considers the sample of respondents who have provided their national ID. The Table excludes the cases in which a respondent records a zero outcome in one of the data sources.

3.3. Studying the impact of financial literacy on the quality of self-assessed financial information

To study the impact of financial literacy on the quality of self-assessed financial information, we rely on the Survey-Administrative dataset. Our outcome variable is the absolute proportional differences of loan amounts between the Survey and the administrative records (Madeira et al., 2022). Specifically, let $y_{i,t,d,A-S}$ be the ratio of the absolute difference between the loan amounts in each data-set, as a proportion of its mean value:

$$y_{i,t,d,A-S} := \frac{\left|Y_{i,t,d,Admin} - Y_{i,t,d,Survey}\right|}{(Y_{i,t,d,Admin} + Y_{i,t,d,Survey})/2},$$

with $Y_{i,t,d,Admin}$ and $Y_{i,t,d,Survey}$ representing the loan amounts of borrower i at time t and debt type d, for the respective Survey and administrative reports, divided by their mean value. Since there can be disparities between the month at which the administrative data-set is recorded and the date reported in the Survey (see Section 3.1), we take the closest value of $Y_{i,t,d,Admin}$ in a two month window, that is,

$$Y_{i,t,d,Admin} \equiv \underset{\tilde{Y}_{i,t+k,d,Admin}, k\in\{-2,-1,0,1,2\}}{\operatorname{argmin}} \left|\tilde{Y}_{i,t+k,d,Admin} - Y_{i,t,d,Survey}\right|$$

The ratio statistic $y_{i,t,d,A-S}$ has become the most standard way of measuring differences between two data-sets (Törnqvist et al., 1985) or the rate of changes between two time periods when one event can be zero (Davis et al., 2006), such as the case of months where companies report zero earnings. Also, note that $y_{i,t,d,A-S}$ is by definition bounded by 2 (or equivalently 200%) which corresponds to cases in which one of the data sources records a zero outcome.

Table 2 reports, by debt category, the 10, 25, 50 and 75 percentiles, as well as the mean of the ratio $y_{i,t,d,A-S}$ computed for loan amounts, distinguishing by debt type (mortgages, installment loans and credit cards and credit lines). Recall that if a borrower has more than one loan in a certain debt category, we consolidate all loan amounts for each debt type.

Table 2 shows that the median borrower reports debt amounts fairly well in the case of mortgages and installment loans, with the median difference being in the order of 30% in the case of mortgages. It is worth mentioning that part of the discrepancies may be due to administrative costs charged to loans that households do not include in their reports; they only declare the requested amount to the bank. For details on the sources of differences between the Survey and the administrative records, see Madeira et al. (2022). However, the differences between the Survey and the administrative records in the tails of the empirical distributions of $y_{i,t,d,A-S}$ can be substantial. Complementing the evidence in Table 2, Fig. A.1, in Appendix, depicts the probability density function of the absolute proportional differences between the Survey and the Administrative records $y_{i,t,d,A-S}$, obtained using an Epanechnikov kernel and the Silverman's rule for the bandwidth across respondents. The evidence in this Figure indicates that respondents with lower financial literacy levels (that is, those with a financial literacy score below its percentile 75th) exhibit larger discrepancies for the reported loan amounts in the Survey, relative to the administrative records. This is the case for all the loan types we consider (mortgages, credit cards, lines of credit, and consumer installment loans).

The model specification for measuring the impact of financial literacy on the quality of self-assessed financial information is

$$\mathbf{y_t} = \alpha + \gamma\mathbf{FinLit_t} + \mathbf{X_t}\beta + \boldsymbol{\epsilon}_\mathbf{t}, \tag{1}$$

where $\mathbf{y_t}$ is the vector of differences between the Survey and the administrative records for each respondent and debt type (which element is $y_{i,t,d,A-S}$); $\mathbf{FinLit_t}$ is one of the proxies that we consider to measure financial literacy; $\mathbf{X_t}$ is a matrix of respondent-, household- or debt-type-specific characteristics; $\boldsymbol{\epsilon}_\mathbf{t}$ is the vector of error terms and α, β, γ are parameters to be estimated. Because of the evidence presented in Table A.4 showing that there is a positive relation between education and financial literacy, we account for this possible multicollinearity by creating an additional indicator factor for financial education. Precisely, we compute the first principal component (FPC) of our three proxies for financial literacy (namely whether the respondent knows her pension account type, whether the household uses automatic means of payments and the composite INFE financial literacy index), as well as the maximum education level attained by the respondent. We will denote this factor variable as *FPC financial literacy score*.[11] The to-be presented results will hence include an additional model specification incorporating this principal component factor variable for financial education.

As additional explanatory variables, we include demographic characteristics of the respondents, namely sex, a dummy variable for the respondent being married and the respondent's maximum level of education. Note that we will only include this last covariate in some model specifications. In addition, as households' characteristics, we consider the number of generations present in the household (one, two, three or more; for references, see Browning et al., 2014; Kim and Waite, 2016); an indicator variable for the household being interviewed for the first time; whether the household is situated in the Metropolitan region of Santiago; fixed effects for the Survey waves and for debt categories (mortgages, installment loans and credit cards and credit lines). Furthermore, following Eggleston and Reeder (2018), we incorporate the ratio of the number of missing income and asset variables over the total number of income and asset sources of the household and the average amount of rounding in income and asset questions. We add these last two variables to control for unobserved characteristics that may affect measurement errors.

Regarding estimation, we first do ordinary linear model estimation. Next, as a robustness check, we follow a nearest neighbor matching strategy (Thoemmes and Kim, 2011; Zakrison et al., 2018) to further investigate the effect of financial literacy on the differences between the Survey and the administrative records. This matching strategy involves running through the list of treated units and selecting the closest eligible control units to be paired with each treated unit. To run the exercise, the treated group corresponds to the financially literate respondents; the non-treated units are the financially illiterate respondents. To proxy

[11] Principal components are often used in the education literature in general, and in studies of financial literacy (Behrman et al., 2012; Hung et al., 2020), in particular. The issue in this case is that indexes such as the OECD-INFE implicitly apply the same importance weight to all the questions, while the principal component analysis extracts the more robust signal that is common to all the variables and, therefore, it implicitly gives less weight to more noisy measures.

Table 3
Descriptive statistics for the outcome and the independent variables.

Variables	Obs.	Mean	Std. Dev.	Min.	Max.
Outcome variable					
Proportional differences	6154	1.41	0.79	0.00	2.00
Fin. literacy proxies					
Resp. knows her pension fund	6625	0.34	0.48	0.00	1.00
HH. uses automatic payments	6625	0.27	0.44	0.00	1.00
INFE fin. literacy	6625	12.17	1.23	8.85	14.09
FPC fin. literacy score	6619	−0.01	0.99	−1.93	2.00
FPC fin. literacy score above 75	6625	0.24	0.43	0.00	1.00
Demographic variables					
Resp. is a male	6625	0.43	0.50	0.00	1.00
Resp. is married	6625	0.46	0.50	0.00	1.00
Resp.'s education	6619	2.76	1.20	1.00	5.00
Number of generations	6625	1.72	0.70	1.00	3.00
Survey variables					
Interviewed for the first time	6625	0.54	0.50	0.00	1.00
Metropolitan region of Santiago	6625	0.44	0.50	0.00	1.00
Unobservable quality variables					
Average INR — income & assets	6607	0.09	0.20	0.00	1.00
Rounding rate — income & assets	6507	0.88	0.11	0.00	1.00

Notes: The table exhibits the summary statistics of the outcome and explanatory variables. Obs., Std. Dev., and Min. and Max. stand, respectively, for the number of observations, the standard deviation, and the minimum and maximum values of the empirical distribution of the corresponding variable. Resp. stands for respondent, HH. for household, stud. for studies, INR for item non-response, and fin. stands for financial. FPC abbreviates first principal component. INFE is the acronym of International Network on Financial Education. For details on each variable, please refer to Table A.5 in the Appendix.

for financial literacy, we consider the financial literacy index that we obtain from the principal component factor model, that is, the *FPC financial literacy score*. We rely on two alternative definitions of a financially literate respondent, and hence a treated unit: (i) those respondents whose FPC financial literacy score is above the 75th percentile of the empirical distribution of this variable; (ii) those whose FPC financial literacy score is above the median. A financially illiterate respondent is hence one that has a FPC financial literacy score which is below the 75th percentile or the median, depending on the threshold considered.

To identify the group of neighboring respondents for each treated unit, we rely on the same characteristics that we have used before in the linear model estimates (with the exception of education), that is, sex, a dummy variable for the respondent being married, the number of generations present in the household, an indicator variable for the household being interviewed for the first time, whether the household is situated in the Metropolitan region of Santiago, indicator variables for the Survey waves and the debt types, the ratio of the number of missing income and asset variables over the total number of income and asset sources of the household and the average amount of rounding in income and asset questions. Similarity between respondents is hence based on a weighted function of the covariates for each observation. The nearest neighbor matching estimator then imputes the missing potential outcome for each respondent by using an average of the outcomes of similar respondents. Recall that in this exercise the observed and the imputed potential outcomes correspond to the absolute proportional differences between the Survey and the administrative records. Last, we compute the average treatment effect by taking the average of the difference between the observed and the imputed potential outcomes for each respondent; we then average across all respondents.

The next Table presents the descriptive statistics of the outcome variable and the independent variables that we consider in this paper. In the case of the independent variables, we classify them along the financial literacy proxies, demographic variables, survey factors and unobservable respondents' characteristics related to their propensity to round and not to respond.

In the next section, we present our empirical findings. First, Section 4.1 exhibits the ordinary linear model estimates. Next, Section 4.2 discusses the robustness checks we perform.

4. Empirical findings

4.1. Ordinary linear model estimation

To begin with, Table 4 presents the ordinary linear model estimates for the absolute proportional differences between the Survey and the administrative records. In addition to the demographic, survey and unobservable quality variables as described in Table 3, column one in Table 4 adds our first proxy for financial literacy, that is, whether the respondent knows her pension account type. Column two includes as a proxy for financial literacy whether the household uses automatic means of payments. In turn, column three considers the INFE financial literacy index to capture respondents' financial education, whereas column four in the same Table incorporates, instead, the first principal component which we obtain by computing the factor model that includes our three proxies for financial literacy, as well as the respondents' education level. Note that the model estimates in column four exclude the categorical variable for the respondent's education, the latter being to avoid collinearity between this variable and the factor variable itself measuring financial literacy. Last, column five considers the same model specification than in column four except that instead of relying on the continuous FPC financial literacy score, it includes an indicator variable for whether the respondent registers a FPC financial literacy score above the percentile 75 of the empirical distribution of this variable and zero otherwise. The aim of this last model specification is to enable comparison with the to-be-presented model estimates relying on the nearest neighbor matching strategy to study the causal effect of financial literacy on the absolute proportional differences between the Survey and the administrative records. Recall that this indicator variable will determine the treated and non-treated units. As robustness checks, Table A.6, in Appendix, estimates the same model specifications that in Table 4, except

Table 4
Ordinary linear model estimates for the absolute proportional differences between the Survey and the administrative records.

Variables	(1)	(2)	(3)	(4)	(5)
Resp. knows her pension fund	−19.90***				
	(2.31)				
HH. uses automatic payments		−15.25***			
		(2.57)			
INFE fin. literacy			−14.31***		
			(2.20)		
FPC fin. literacy score				−18.56***	
				(1.19)	
FPC fin. literacy score above 75					−24.90***
					(2.37)
Resp. is a male	−7.69***	−8.90***	−1.25	−4.19*	−7.63***
	(2.32)	(2.32)	(2.64)	(2.34)	(2.36)
Resp. is married	2.82	4.31*	4.60**	4.95**	4.64**
	(2.30)	(2.33)	(2.32)	(2.30)	(2.35)
Two generations	−2.41	−3.16	−0.36	−2.35	−1.43
	(2.44)	(2.46)	(2.51)	(2.42)	(2.46)
Three or more generations	3.99	3.34	7.48**	4.14	5.93*
	(3.30)	(3.32)	(3.40)	(3.26)	(3.36)
Average INR − income & assets	34.50***	40.04***	41.67***	38.96***	39.67***
	(6.40)	(6.45)	(6.44)	(6.35)	(6.41)
Rounding rate − income & assets	5.43	8.30	9.04	6.67	7.11
	(10.62)	(10.92)	(10.75)	(10.68)	(10.77)
Resp. has secondary stud.	−16.74***	−18.17***	3.30		
	(4.13)	(4.12)	(5.42)		
Resp. has technical stud.	−24.66***	−26.06***	7.34		
	(4.72)	(4.77)	(7.49)		
Resp. has bachelor stud.	−30.16***	−30.29***	5.01		
	(4.08)	(4.22)	(7.63)		
Resp. has postgraduate stud.	−42.11***	−42.28***	−9.86		
	(4.92)	(5.09)	(8.01)		
R^2	0.06	0.06	0.06	0.07	0.05
Observations	6,103	6,103	6,103	6,103	6,104

Notes: This Table exhibits the ordinary linear model estimates for the absolute proportional differences between the Survey and the administrative records. As demographic and survey variables, model estimates include gender; a dummy variable for the respondent being married; the respondent's maximum level of education (in columns (1) to (3)); the number of generations present in the household; an indicator variable for the household being interviewed for the first time; whether the household is situated in the Metropolitan region of Santiago; and fixed effects for the Survey waves and for debt categories. Furthermore, we incorporate unobservable quality variables (the ratio of the number of missing income and asset variables, and the average amount of rounding in income and asset questions). Column (1) includes as a proxy for financial literacy whether the respondent knows her pension account type; column (2) considers whether the household uses automatic means of payments and column (3) relies on the composite INFE financial literacy index. In turn, column (4) includes the FPC financial literacy score, whereas the proxy for financial literacy in column (5) is the binary variable FPC financial literacy score above 75. The Table does not report the intercept, the fixed effect for the debt categories, for the Survey waves and for the Metropolitan region of Santiago. Standard errors are in parentheses. Errors are clustered at Survey wave − respondent level. *** $p<0.01$, ** $p<0.05$, * $p<0.1$. Resp. stands for respondent, HH. for household, stud. for studies, INR for item non-response, and fin. stands for financial. FPC abbreviates first principal component. INFE is the acronym of International Network on Financial Education. For details on each variable, please refer to Table A.5 in the Appendix.

that Table A.6 includes fixed effects for the interviewers. Unfortunately, this information is not available for the 2011 wave. Therefore, model estimates in Table A.6 include only the 2014 and 2017 waves of the Chilean Household Finance Survey.

The main conclusion to extract from Table 4 is that the various proxies for financial literacy are statistically significant and negative, as expected. Results hence indicate that a more financially literate respondent provides a more accurate response about her liabilities. In addition, Table 4 shows that the categorical variable capturing the maximum education level of the respondent tends to exert a stronger effect on the absolute proportional differences when we include the financial literacy proxies whether the respondent knows her individual pension account type or whether the household uses automatic means of payment. In contrast, the categorical variable for education appears to be less significant in the model estimate (3). The way to interpret this finding is that the INFE financial literacy measure may provide a more complete assessment of individuals' financial education, which in turn might explain why the categorical variable education does no longer appear significant when including in the model specification the INFE financial literacy measure or its variants.

To complement previous findings, Table 5 examines the impact of financial literacy on the differences between the Survey and the administrative distinguishing between the two possible types of errors, namely, whether the total loan amount of a given respondent and debt category is present in one data source only (the Survey or the administrative records) or whether the reported loan amounts in the Survey are different from the ones recorded in the administrative records. We refer to the first error as differences in the extensive margin and to the second one as discrepancies in the intensive margin. In particular, within the intensive margin, one could further distinguish between those respondents that over-report (the reported total loan amount in the Survey is larger than the total amount in the administrative records for a given individual and debt category) from those respondents that under-report (which occurs when the total reported loan amount in the Survey is smaller than the total debt that appears in the administrative records for a given individual and debt category). To account for these alternative sources of discrepancies, we create new indicator and categorical variables. First, we define a binary variable that takes the value of one if a positive loan amount of a given debt type belonging to a certain respondent is present in both data sources and zero otherwise. We refer to this variable as *Debt in Admin and Survey*. Second, we create a categorical variable that distinguishes among (i) those observations that appear only in the Survey (Survey only); (ii) those observations that are only in the administrative records (Admin only); (iii) those observations that register a lower amount of reported debt in the Survey, relative to the administrative records (under-report in Survey); (iv) those observations that exhibit a larger amount of reported debt in the Survey, relative to the administrative records (over-report in Survey).

Table 5 exhibits the ordinary linear model estimates for the absolute proportional differences between the Survey and the administrative records. All model estimates in this Table rely on the first principal component financial literacy score (FPC fin. literacy score). For comparison, column one in Table 5 exhibits the fourth model specification in Table 4. Starting from the same demographic, survey and unobservable quality variables than in the fourth model specification in Table 4, column two incorporates the interaction between the indicator variable for the non-existence of errors in the extensive margin (*Debt in Admin and Survey*) and the FPC financial literacy score. Last, column three interacts the financial literacy proxy with the categorical variable that distinguishes among those observations that appear in one data source only (Survey only or Admin only); the under-reports in Survey; and the over-reports in the Survey.

Table 5 reveals several interesting findings. To begin with, it shows that financial literacy is associated with more accurate responses when the respondent has correctly reported the debt type and the debt owner (that is, when there is a positive debt amount both in the Survey and in the administrative records, which results in the dummy variable taking the value of one). In contrast, when the respondent incorrectly reports the loan type and/or the debt owner (which leads to the total loan amount of a given respondent and debt category being present in one data source only), there is a positive relation between financial literacy and the differences between the Survey and the administrative records in the extensive margin.

One possible way to interpret this positive impact of financial literacy on the differences in the extensive margin is that respondents do not have enough confidence on the study. Specifically, if respondents are concerned about being identified by their responses, or if they have a general aversion to sharing financial information, even anonymously, these respondents may not want to provide accurate responses (Barceló, 2006; Gideon et al., 2017). For instance, a respondent with privacy concerns may *deliberately* abstain from reporting a certain loan in the Survey or may choose to incorrectly report the debt type, the debt provider or the owner of a given debt. This might in turn explain why despite being financially literate, a respondent might not want to correctly report a loan. Another possible explanation for the distinct impact of financial literacy on the differences in the extensive margin might be that the respondent might *unintentionally* forget to report some of the loan(s) the household holds. Under this interpretation, the higher the education level of the respondent, the larger her income and hence, the more likely it may be that the members of her household have good access to the debt market. This could in turn increase the likelihood that the respondent forgets to report some loans of the household. The latter effect may occur, for instance, when the amount of the loan(s) is (are) small.

Second, the model estimates in the third column of results in Table 5 reveal that the impact of financial literacy is of equal importance both for the under- and over-reports in the Survey, conditional on the respondent having correctly reported the debt owner and the debt type. This is an interesting finding as it demonstrates that financially literate households provide responses which have, on average, smaller errors, without exhibiting any systematic pattern on the sign of these errors. Furthermore, Table 5 shows that differences in the intensive margin between the Survey and the administrative records are larger if the respondent is married and if there are multiple generations co-existing in the household. The latter hence confirms previous findings in the literature (Madeira et al., 2022) that married couples have more complex finances and often, the members of the couple do not fully know or understand the financial details of the loans of the other household members. Table 5 also indicates that the differences between the Survey and the administrative records are increasing in the item non-response rate for income and assets items of the households, with these being proxies for unobserved characteristics that may affect measurement errors.

4.2. Robustness checks

We run a battery of robustness checks. First, to address the possible endogeneity of financial literacy, we perform the Lewbel instrumental-variable regression analysis (Lewbel, 2012). Unfortunately, we do not have valid external instruments. As a result, we only include model-based instruments for financial literacy. Table 6 exhibits the IV model estimates. Specifically, as alternative proxies for financial literacy, Table 6 includes the composite INFE financial literacy index (column one), the FPC financial literacy score (column two) and the binary variable for the FPC financial literacy score being above its percentile 75th (column three). Overall, results in Table 6 show that the coefficient estimates remain qualitatively similar to the ones reported in Table 4. In particular, the instrumented financial literacy proxies are always negative and, with one exception, they are statistically significant. Furthermore, the Hansen J-statistic test does not reject the null hypothesis that the over-identifying restrictions are valid for the FPC financial literacy score and for the dummy variable with the FPC financial literacy score being above its percentile 75th. However, when comparing the IV coefficient estimates for the latter two variables (FPC financial literacy score and FPC financial literacy score above 75) with respect to their corresponding OLS estimates in Table 4, we cannot derive definite conclusions. This is because for the first variable (FPC financial literacy score), we find a larger effect size of the IV estimate relative to the corresponding OLS estimate, whereas the opposite is true in the case of the second financial literacy proxy (FPC financial literacy score above 75).

Second, to study the psychometric properties of our financial literacy indexes and the validity of our results, we conduct an Item Response Theory (IRT) analysis for the categories of the OECD-INFE financial literacy proxy using the raw data of the Survey of Financial Capabilities. To obtain the composite IRT Financial Education index, we rely on a hybrid approach of a graded response model for the four Financial Attitude questions (which are on an ordinal scale between 1 and 5) coupled with a three-parameter logistic model for the eight Financial Knowledge questions, the eight Financial Behavior questions, and the two Financial Search questions. We compute in a similar fashion the corresponding IRT Financial Knowledge, IRT Financial Behavior and IRT Financial Search indexes, using three-parameter logistic models, while we rely on a graded response model to estimate the IRT Financial Attitude index. Next, we calculate the mean IRT probability that a household has a given financial literacy category for each demographic group, according to their age (10 year brackets), sex, education (5 brackets) and income quartile. Last,

Table 5
OLS regression estimates for the absolute proportional differences between the Survey and the administrative records.

	(1)	(2)	(3)
FPC fin. literacy score	−18.56*** (1.19)		
Debt in Admin and Survey = 1#FPC fin. literacy score		−63.01*** (1.83)	
Debt in Admin and Survey = 0#FPC fin. literacy score		14.90*** (1.04)	
Survey only#FPC fin. literacy score			15.38*** (1.61)
Over-report in Survey#FPC fin. literacy score			−63.25*** (2.40)
Under-report in Survey#FPC fin. literacy score			−63.15*** (2.05)
Admin only#FPC fin. literacy score			14.68*** (1.07)
Resp. is a male	−4.19* (2.34)	−2.03 (1.92)	−1.79 (1.92)
Resp. is married	4.95** (2.30)	6.31*** (1.86)	6.22*** (1.86)
Two generations	−2.35 (2.42)	−0.84 (1.96)	−0.86 (1.96)
Three or more generations	4.14 (3.26)	6.84** (2.77)	6.72** (2.77)
Average INR — income & assets	38.96*** (6.35)	18.82*** (5.12)	18.77*** (5.12)
Rounding rate — income & assets	6.67 (10.68)	−1.31 (8.54)	−1.53 (8.53)
R^2	0.07	0.36	0.36
Observations	6,103	6,103	6,100

Notes: This Table exhibits the ordinary linear model estimates for the absolute proportional differences between the Survey and the administrative records, distinguishing between the two possible types of errors, namely, whether the total loan amount of a given respondent and debt category is present in one data source only (differences in the extensive margin) or whether the reported loan amounts in the Survey are different from the ones recorded in the administrative records (differences in the intensive margin). All model estimates in this Table rely on the first principal component financial literacy score (FPC fin. literacy score). For comparison, column (1) exhibits the fourth model specification in Table 4. Considering the same demographic, survey and unobservable quality variables than in the fourth model specification in Table 4, column (2) incorporates the interaction between a binary variable that takes the value of one if a positive loan amount of a given debt type belonging to a certain respondent exists in both data sources (and zero otherwise) and the FPC financial literacy score. This indicator variable is *Debt in Admin and Survey*. Column (3) interacts the same financial literacy proxy with a categorical variable that distinguishes among (i) those observations that appear only in the Survey (Survey only); (ii) those observations that are only in the administrative records (Admin only); (iii) those observations that register a lower reported debt amount in the Survey, relative to the administrative records (under-report in Survey); (iv) those observations that exhibit a larger reported debt amount in the Survey, relative to the administrative records (over-report in Survey). The Table does not report the intercept, fixed effects for the debt categories, for the Survey waves and for the Metropolitan region of Santiago. Standard errors are in parentheses. Errors are clustered at Survey wave — respondent level. *** p<0.01, **p<0.05, * p<0.1. Resp. stands for respondent, stud. for studies, INR for item non-response, and fin. stands for financial. FPC abbreviates first principal component. The symbol # denotes an interaction term. INFE is the acronym of International Network on Financial Education. For details on each variable, please refer to Table A.5 in the Appendix.

we match the estimated mean IRT probabilities for each demographic group with the corresponding group of each respondent in the Chilean Household Finance Survey.

Table A.7, in Appendix, exhibits the mean IRT probabilities that households in a given socio-economic group (groups are formed based on households' income quintile or their education level) have a given financial literacy category. Interestingly, the Table shows that all the IRT financial literacy indexes (whether the overall Financial education or its four sub-indexes: Attitudes, Behavior, Knowledge, Search), are increasing in the education level and in the income quintile of the households. Furthermore, we estimate a linear regression model to assess the effect of the IRT financial education on the Survey respondents' mis-reporting of loans, using the Lewbel IV method to instrument financial literacy. Specifically, the financial literacy proxy in this case is the IRT probability that a household has the composite financial literacy index which results from estimating a three-parameter logistic model on the questions from the Behavior + Knowledge + Search modules.

Table 6, last column, exhibits the results. The Table confirms the previous findings as it shows that the instrumented IRT Financial Education index has a significantly negative impact on the absolute proportional differences between the Survey and the administrative records.[12]

Third, as an additional robustness check, we further test the causal interpretation of our results regarding the negative impact of financial literacy on the inaccuracy of loan reporting. Table A.10, in Appendix, exhibits the average treatment effect of financial literacy on the proportional differences between the Survey and the administrative records. The estimation follows the nearest neighbor matching strategy detailed in Section 3. We

[12] As additional robustness checks, in unreported analyses, we consider alternative OLS and Lewbel IV model specifications with various ways of modeling the INFE financial literacy proxy. Specifically, we consider the full OECD-INFE Financial Index (A+B+K+S), the more traditional OECD-INFE Financial Knowledge Index, and their equivalents obtained as a probability from the IRT model. Importantly, results remain qualitatively similar and statistically significant, relative to the estimates exhibited in Tables 4 and 6. Results are available from the authors upon request.

Table 6
Lewbel IV estimates for the absolute proportional differences between the Survey and the administrative records.

Variables	(1)	(2)	(3)	(4)
Resp. is a male	−4.994	1.531	−7.893***	−5.434*
	(3.907)	(4.060)	(2.372)	(3.160)
Resp. is married	3.673	7.952***	3.952*	3.351
	(2.419)	(2.817)	(2.361)	(2.334)
Two generations	−1.457	−0.707	−2.550	−1.535
	(2.665)	(2.546)	(2.464)	(2.576)
Three generations	6.011*	5.514*	4.113	5.743*
	(3.608)	(3.286)	(3.341)	(3.446)
Average INR — income & assets	40.64***	37.56***	39.42***	40.07***
	(6.445)	(6.387)	(6.467)	(6.401)
Rounding rate — income & assets	9.081	3.631	7.726	9.302
	(10.79)	(10.76)	(10.76)	(10.74)
Resp. has secondary stud.	−7.387	23.23*	−20.71***	−0.944
	(9.868)	(13.38)	(4.104)	(10.50)
Resp. has technical stud.	−10.03	47.91**	−27.25***	0.119
	(15.48)	(23.43)	(4.778)	(16.54)
Resp. has bachelor stud.	−14.12	62.86**	−26.94***	−4.733
	(16.76)	(29.36)	(4.788)	(16.98)
Resp. has postgraduate stud.	−28.34*	65.31*	−38.17***	−16.70
	(16.51)	(34.10)	(5.882)	(18.00)
INFE fin. literacy	−7.947			
	(5.417)			
FPC fin. literacy score		−42.24***		
		(12.30)		
FPC fin. literacy score above 75			−15.44***	
			(3.951)	
IRT fin. literacy probability				−252.5**
				(126.0)
Observations	6,103	6,103	6,103	6,103
R^2	0.0541	0.0612	0.0537	0.0550
Hansen J-statistic	26.330**	13.257	10.473	26.344**

Notes: This Table exhibits the Lewbel IV model estimates for the absolute proportional differences between the Survey and the administrative records. As demographic and survey variables, estimates include gender; a dummy variable for the respondent being married; the respondent's maximum level of education; the number of generations present in the household; an indicator variable for the household being interviewed for the first time; whether the household is situated in the Metropolitan region of Santiago; and fixed effects for the Survey waves and for debt categories. Furthermore, we incorporate unobservable quality variables (the ratio of the number of missing income and asset variables, and the average amount of rounding in income and asset questions). Column (1) includes as a proxy for financial literacy the composite INFE financial literacy index. In turn, column (2) includes the FPC financial literacy score, whereas column (3) incorporates as proxy for financial literacy the binary variable for the FPC financial literacy score being above its 75th percentile. Last, column (4) relies on the IRT probability that a household has the composite financial literacy index that results from estimating a three-parameter logistic model on the questions from the Behavior + Knowledge + Search modules. The Table does not report the intercept, the fixed effect for the debt categories, for the Survey waves and for the Metropolitan region of Santiago. Standard errors are in parentheses. Errors are clustered at Survey wave — respondent level. *** p<0.01, **p<0.05, * p<0.1. Resp. stands for respondent, HH. for household, stud. for studies, INR for item non-response, and fin. stands for financial. FPC abbreviates first principal component. INFE is the acronym of International Network on Financial Education. For details on each variable, please refer to Table A.5 in the Appendix.

Table A.1
AAPOR response rates.

Year	2011	2014	2017
Response rate 1	0.400	0.641	0.648

Notes: This Table reports AAPOR response rates 1 (The American Association for Public Opinion Research. 2016. Survey Outcome Rate Calculator 4.0.) for the 2011, 2014 and 2017 waves of the Chilean Household Finance Survey.

consider as the treated units the financially literate respondents and the non-treated units as the financially illiterate respondents. To measure financial literacy, we consider the first principal component of our three financial literacy proxies together with the categorical variable for the maximum level of education attained by the respondent (FPC financial literacy score). As explained above, we rely on two alternative definitions of treated units: (i) those whose FPC financial literacy score is above the 75th percentile of the empirical distribution of this variable; (ii) those respondents whose FPC financial literacy score is above the median. We include the same demographic, survey and unobservable quality variables that we include in the model specification in Table 4. The symbol (+) indicates the inclusion of interviewer fixed effects and the exclusion of the 2011 Survey wave, given that the interviewers' information is not available for the year 2011. Table A.9, in Appendix, assesses the balance after the computations of the treatment effects, by comparing means in the raw and balanced datasets.

Results in Table A.10 provide additional support for the negative effect of financial literacy on households' loan misreporting. This is because the average treatment effects for the financial literacy score above the 75th percentile or the median are always statistically significant and negative at the 1% level. Importantly, this result holds regardless of the inclusion or not of the interviewers' fixed-effects, or of the threshold we rely on to identify the treated and non-treated units. Summing up, the robustness checks presented here aim at assessing the validity of the results we exhibit in Table 4. Indeed, we show that the IV estimates

Table A.2
Mean comparisons according to different survey samples.

Variables	Survey	Survey with ID	Survey-Admin matched data: With Debt in the Admin.
Resp. is a male	0.409 (0.004)	0.420 (0.006)	0.498 (0.009)
Resp.'s years of education	12.882 (0.038)	12.769 (0.048)	14.630 (0.074)
Resp.' age	49.914 (0.144)	48.983 (0.183)	49.945 (0.264)
Resp. is married	0.463 (0.004)	0.452 (0.006)	0.522 (0.009)
Metropolitan region of Santiago	0.499 (0.004)	0.461 (0.006)	0.468 (0.009)
Wealth Stratum 1[1]	0.375 (0.004)	0.406 (0.005)	0.270 (0.008)
Wealth Stratum 2[2]	0.234 (0.004)	0.239 (0.005)	0.219 (0.008)
Wealth Stratum 3[3]	0.391 (0.004)	0.354 (0.005)	0.511 (0.009)
Resp. does not have pension fund	0.387 (0.004)	0.374 (0.005)	0.285 (0.008)
Resp. knows her pension fund	0.339 (0.004)	0.346 (0.005)	0.477 (0.009)
Resp. does not know her pension fund	0.273 (0.004)	0.279 (0.005)	0.238 (0.008)
HH. uses automatic payments	0.225 (0.004)	0.227 (0.005)	0.425 (0.009)

Notes: This Table reports, for different socio-demographic variables, the means and the standard errors (in parenthesis) of the total number of the Survey respondents (second column), the number of respondents who provided a correct ID number (third column), and the number of respondents with a correct ID number and positive amounts of debt in the administrative dataset (fourth column). Notes:[1] Wealth stratum 1 denotes 1–50 percentile of wealth distribution.[2] Wealth stratum 2 denotes 51–80 percentile of wealth distribution.[3] Wealth stratum 3 denotes 81–99 percentile of wealth distribution. Resp. stands for respondent. HH uses automatic payments stands for household uses automatic bill payment methods, a credit card and/or checking account. The Table does not include expansion weights.

Table A.3
OECD-INFE financial literacy indexes.

	Attitude	Behavior	Knowledge	Search	Composite
	A	B	K	S	B+K+S
All respondents	3.05	5.78	5.16	1.23	12.17
Resp. income quintile 1	3.17	5.46	4.99	1.01	11.46
Resp. income quintile 2	3.12	5.43	4.95	1.02	11.40
Resp. income quintile 3	3.06	5.61	5.07	1.15	11.83
Resp. income quintile 4	2.95	6.01	5.29	1.39	12.69
Resp. income quintile 5	2.88	6.39	5.50	1.57	13.46
Resp. has primary school	3.40	4.85	4.58	0.69	10.12
Resp. has secondary school	3.13	5.59	5.07	1.11	11.78
Resp. has technical stud.	2.77	5.95	5.44	1.45	12.83
Resp. has graduate stud.	2.95	6.28	5.42	1.45	13.16
Resp. has postgraduate stud.	2.75	6.34	5.30	1.62	13.27

Notes: This Table exhibits the mean financial literacy sub-indexes Attitude, Behavior, Knowledge, and Search. The Table also reports the mean for the composite index that results from adding the categories Behavior + Knowledge + Search (last column). The Table reports these mean sub-indexes and the composite index for all of the respondents and for the respondents being classified by income quintile (poorest quintile = 1, wealthiest quintile = 5) and by respondents' maximum education level attained. Resp. stands for respondent. The Table considers the sample of respondents who have provided their national ID.

and the average treatment effects for financial literacy are always negative and, with one exception, they are statistically significant.

5. Conclusions and discussion

This work uses a unique matched Survey and loan administrative dataset to analyze how financial literacy impacts the quality of the Chilean households' self reported debt information. Using several proxies for financial literacy, such as the OECD INFE measure of financial education, the respondents' knowledge of their personal pension accounts' type and the use of electronic means of payments, we find that financial literacy is positively associated with the accuracy of Survey loan reports, controlling for respondents' education, civil status, gender and household size, among other factors. Our results are robust to (i) conducting the Lewbel instrumental-variable regression estimation to address the possible endogeneity of the financial literacy measures; (ii) to relying on item response theory models to derive an alternative scale for our OECD-INFE financial literacy proxy, among others; (iii) using a nearest neighbor matching estimator to study the effect of financial literacy on households' loan reporting.

Our results have several policy implications for Survey administrators, regulators, policy makers, and researchers. To begin with, household finance surveys have become increasingly available across many countries, but the quality of the self-reported information is still debated (Zinman, 2009; Fesseau and Mattonetti, 2013; Brown et al., 2015). Our work suggests that financial literacy efforts could be an important step towards improving survey quality. For instance, it is well known that both assets and debts are heavily under-reported in household finance surveys (Neri and Monteduro, 2013; Madeira et al., 2022), therefore, there is a substantial margin for financial literacy to improve the reporting of financial variables. Our results can also be seen as long-lasting effects, since our INFE proxies for financial education come from averages obtained for each demographic group on a questionnaire for which the respondents were untrained. A specific program of financial education for survey respondents is likely to obtain even stronger results.

Second, our results suggest that one channel in which financial education affects outcomes and behaviors (Kaiser et al., 2021)

Table A.4
Relation between education and our financial literacy proxies.

	Resp. knows her pension fund	HH. uses automatic payments	INFE fin. literacy
All respondents	34.46	26.62	12.17
Resp. has primary school	11.35	1.98	10.12
Resp. has secondary school	26.63	12.68	11.78
Resp. has technical stud.	43.21	30.55	12.83
Resp. has graduate stud.	45.05	46.09	13.16
Resp. has postgraduate stud.	66.20	66.67	13.27

Notes: This Table exhibits for each respondents' educational category, the percentage of respondents who know their pension account type (column two), the percentage of respondents' households who use automatic means of payments (column three), and the mean composite index of financial literacy (Behavior + Knowledge + Search, column four). Resp. stands for respondent, HH. for household, stud. for studies, and fin. stands for financial. INFE is the acronym of International Network on Financial Education. The Table considers the sample of respondents who have provided their national ID.

Table A.5
Variables' description.

Variable	Description
Outcome variable	
Proportional differences	Absolute difference between the loan amounts in the administrative records and the Survey, as a proportion of their mean values. Negative (positive) values indicates over-reported (under-reported) values of debt in the Survey. The variable is computed for each debt category.
Financial literacy proxies	
Resp. knows her pension fund	Binary variable that takes the value of one if the respondent knows her pension account type.
HH. uses automatic payments	Binary variable that takes the value of one if the at least one member of the household uses automatic bill payment methods (including automatic checking account and/or credit card payments).
INFE fin. literacy	Composite index that results from adding the categories Behavior, Knowledge, and Search from the financial literacy variables developed by the OECD-International Network on Financial Education or INFE.
FPC fin. literacy score	First principal component of the following variables: Whether the respondent knows her pension account type, the use of automatic payments, the INFE financial literacy, and respondent's education.
FPC fin. literacy score above 75	Binary variable that takes the value of one for respondents whose FPC fin. literacy score is above the 75th percentile.
Demographic variables	
Resp. is a male	Binary variable that takes the value of one if the respondent is a male.
Resp. is married	Binary variable that takes the value of one if the respondent is married.
Resp.'s education	Categorical variable for the respondent's highest level of education attained. The variable takes the value of one if the respondent's highest level of education is primary school, two for secondary education, three for technical studies, four for bachelor studies, and five if the respondent's highest level of education is postgraduate.
Number of generations	Number of generations present in the household, the variable takes the value one, two, and three; three for three or more generations present in the same house.
Debt category	Categorical variable for the type of debt. The categories are mortgages, installment loans, credit card and credit line loans.
Survey variables	
Interviewed for the first time	Dummy variable that takes the value of one if the respondent has been interviewed for the first time.
Metropolitan region of Santiago	Binary variable that takes the value of one if the respondent lives in the metropolitan region of Santiago.
Unobservable quality variables	
Average INR — income & assets	Average rate of missing values in income and asset items, both at household and individual level.
Rounding rate — income & assets	Measure of rounding intensity in income and asset items, both at household and individual level.

Notes: Resp. stands for respondent, HH. for household, stud. for studies, INR for item non-response, and fin. stands for financial. FPC abbreviates first principal component. INFE is the acronym of International Network on Financial Education.

could be from the higher awareness that consumers have about their current financial situation, such as knowledge about the amounts and maturity of their debts. For instance, it is well known in the literature that credit cards are one of the loan types with higher mis-reporting (Zinman, 2009; Madeira et al., 2022), higher default rates and "hidden" fees charged to consumers (Badarinza et al., 2016). Therefore, financial education that provides borrowers a better knowledge of the loan amounts

Table A.6
Ordinary linear model regression estimates for the absolute proportional differences between the Survey and the administrative records, with interviewer fixed effect (and without 2011).

Variables	(1)	(2)	(3)	(4)	(5)
Resp. is a male	−8.88***	−10.31***	−1.32	−5.55**	−9.69***
	(2.49)	(2.48)	(2.84)	(2.51)	(2.52)
Resp. is married	3.75	5.27**	5.82**	6.03**	5.30**
	(2.45)	(2.49)	(2.46)	(2.46)	(2.51)
Two generations	−0.47	−1.11	1.98	−0.47	0.76
	(2.61)	(2.65)	(2.66)	(2.60)	(2.65)
Three or more generations	4.95	4.73	8.74**	5.40	8.70**
	(3.80)	(3.80)	(3.87)	(3.73)	(3.83)
Average INR – income & assets	32.22***	37.46***	39.84***	35.41***	36.40***
	(8.39)	(8.46)	(8.46)	(8.25)	(8.41)
Rounding rate – income & assets	−2.71	0.16	0.13	−2.61	−4.08
	(12.97)	(13.31)	(13.04)	(13.12)	(13.38)
Resp. has secondary stud.	−24.93***	−26.74***	−3.04		
	(4.71)	(4.73)	(5.96)		
Resp. has technical stud.	−29.44***	−30.64***	6.63		
	(5.31)	(5.40)	(8.03)		
Resp. has bachelor stud.	−37.47***	−38.16***	2.24		
	(4.72)	(4.88)	(8.16)		
Resp. has postgraduate stud.	−46.78***	−48.27***	−10.36		
	(5.53)	(5.66)	(8.63)		
Resp. knows her pension fund	−19.88***				
	(2.53)				
HH. uses automatic payments		−13.91***			
		(2.70)			
INFE fin. literacy			−16.46***		
			(2.38)		
FPC fin. literacy score				−19.05***	
				(1.33)	
FPC fin. literacy score above 75					−22.67***
					(2.58)
R^2	0.14	0.13	0.13	0.14	0.12
Observations	5,128	5,128	5,128	5,128	5,128
Interviewer effect	Yes	Yes	Yes	Yes	Yes

Notes: This Table exhibits the ordinary linear model estimates for the absolute proportional differences between the Survey and the administrative records. Estimates in this Table include interviewers' fixed effects. Given that the interviewers' information is not available for the 2011 wave, the estimates exclude the observations for that year. As demographic, survey and unobservable quality variables, model estimates include gender; a dummy variable for the respondent being married; the respondent's maximum level of education (in columns (1) to (3)); the number of generations present in the household; an indicator variable for the household being interviewed for the first time; whether the household is situated in the Metropolitan region of Santiago; fixed effects for the Survey waves and for the debt categories; the ratio of the number of missing income and asset variables, and the average amount of rounding in income and asset questions. The financial literacy proxies are: Whether the respondent knows her pension account type (column (1)); whether the household uses automatic means of payments (column (2)); the composite INFE financial literacy measure (column (3)), the FPC financial literacy score (column (4)), and the FPC financial literacy score above 75 (column (5)). The Table does not report the intercept, the fixed effect for the Survey waves, for the debt categories and for the Metropolitan region of Santiago. Standard errors are in parentheses. Errors are clustered at Survey wave – respondent level. *** p<0.01, **p<0.05, * p<0.1. Resp. stands for respondent, HH. for household, stud. for studies, INR for item non-response, and fin. stands for financial. FPC abbreviates first principal component. INFE is the acronym of International Network on Financial Education. For details on each variable, please refer to Table A.5 in the Appendix.

may help them pay their credit cards to avoid default and minimize fees (Agarwal et al., 2020). More financially educated respondents may manage better their credit cards and may avoid costs such as the inefficient use of multiple cards due to inattention or mental accounting (Ponce et al., 2017).

Third, we find that financial illiteracy leads to measurement errors in households' self-reports. Therefore, when researchers are interested in the impact of a financial education program on financial behaviors, measurement error will affect their ability to estimate unbiased causal effects. Lastly, our results indicate that financial literacy may be correlated to some omitted psychological individuals' traits (Fernandes et al., 2014), which in turn may lead to biased estimates for the impact of financial education on (self-reported) financial behavior. The consequence of the last two points is that when studying the causal effect of financial literacy (or a financial education program) on behaviors, researchers may need to turn to instrumental variables or experimental designs to account for the endogeneity of financial literacy and/or omitted variable bias.

Overall, a promising agenda of research is still to be pursued to analyze the benefits of financial education on households' financial choices (Hastings et al., 2013; Gomes et al., 2021) and on how to improve household surveys (Madeira et al., 2022).

Table A.7
Mean IRT probabilities that a household has a given financial literacy category.

	Financial literacy indexes using IRT methods					
	Attitude A	Behavior B	Knowledge K	Search S	Education (B+K+S)	Education (A+B+K+S)
All households	35.9	85.3	73.0	23.3	72.9	72.5
Resp. income quintile 1	28.9	82.7	71.1	19.1	70.3	68.0
Resp. income quintile 2	32.9	83.8	71.7	20.5	71.2	69.9
Resp. income quintile 3	35.7	84.9	72.6	23.1	72.5	72.1
Resp. income quintile 4	38.6	86.4	73.8	25.6	74.0	74.4
Resp. income quintile 5	42.2	88.3	75.4	27.6	75.8	77.3
Elementary education	23.8	80.8	68.5	16.5	68.7	63.8
Secondary education	34.2	85.0	72.4	22.1	72.2	71.7
Technical or Some college	44.7	86.4	76.1	27.6	74.5	76.7
College education	41.0	88.1	75.7	27.3	75.7	77.2
Post-graduate education	48.5	88.4	73.4	29.4	76.0	78.4

Notes: This Table exhibits the mean IRT probabilities for the financial literacy sub-indexes Attitude, Behavior, Knowledge, and Search. The Table also reports the mean IRT probability for the global composite index and for the composite index that results from adding the categories Behavior + Knowledge + Search (last two columns). The Table reports these mean probabilities for the sub-indexes and the composite indexes for all of the respondents and for the respondents being classified by income quintile (poorest quintile = 1, wealthiest quintile = 5) and by respondents' maximum education level attained. Resp. stands for respondent. The Table considers the Survey-Admin sample.

Table A.8
Correlation matrix for the different indexes of financial literacy: OECD-INFE, IRT model, and the FPC financial literacy score.

	Attitude	Behavior	Knowledge	Search	Educ.	Educ. all	FPC
Top panel: OECD-INFE indexes							
Attitude	1						
Behavior	−0.763***	1					
Knowledge	−0.694***	0.887***	1				
Search	−0.813***	0.892***	0.895***	1			
Educ. (B+K+S)	−0.786***	0.974***	0.954***	0.957***	1		
Educ. all (A+B+K+S)	−0.688***	0.965***	0.957***	0.932***	0.989***	1	
FPC fin. literacy score	−0.736***	0.899***	0.840***	0.867***	0.907***	0.891***	1
Bottom panel: Item-response theory (IRT) model indexes							
Attitude	1						
Behavior	0.644***	1					
Knowledge	0.666***	0.809***	1				
Search	0.868***	0.772***	0.860***	1			
Educ. (B+K+S)	0.775***	0.942***	0.897***	0.932***	1		
Educ. all (A+B+K+S)	0.900***	0.861***	0.891***	0.968***	0.961***	1	
FPC fin. literacy score	0.765***	0.839***	0.807***	0.870***	0.911***	0.897***	1

Notes: The Table in the top panel exhibits the correlation coefficients among the financial literacy sub-indexes and the composite indexes (B+K+S), (A+B+K+S) and the FPC financial literacy score The individual indexes are Attitude (A), Behavior (B), Knowledge (K), and Search (S). The Table in the bottom panel reports the correlation coefficients among the IRT probability indexes. FPC stands for first principal component and Educ. for education. The Tables consider the Survey-Admin sample.

CRediT authorship contribution statement

Carlos Madeira: Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Resources, Data curation, Writing – original draft, Writing – review & editing, Visualization, Supervision, Project administration, Funding acquisition. **Paula Margaretic:** Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Resources, Data curation, Writing – original draft, Writing – review & editing, Visualization, Supervision, Project administration, Funding acquisition.

Appendix

A.1. Financial literacy in the survey of financial capabilities

The Survey of Financial Capabilities measured in 2016 an extensive set of financial literacy indexes for 1224 Chilean household. The SCF followed closely the OCDE-INFE methodology (Atkinson and Messy, 2012; OECD, 2020). The OECD-INFE methodology is the result of a multidisciplinary contribution, reflecting the level of financial literacy in a comprehensive manner. The International Network for Financial Education questionnaire, widely adopted around the world, measures four areas of financial literacy: Knowledge, behavior, search and attitudes, which are deemed necessary to make sound financial decisions and achieve personal well-being. According to the OECD methodology, there are no penalties for wrong answers and therefore the missing answers ("don't' know") are treated the same as the wrong ones (OECD, 2020).

The Financial Attitudes index captures attitudes towards saving and long-term planning, being obtained as the sum to four questions. Specifically, the questions ask whether the respondent "disagrees with the following attitude statements: (1) I find it more satisfying to spend than save it for the long term; (2) I tend to live for today and let tomorrow take care of itself, (3) Money is there to be spent; (4) I am willing to risk part of my money when I make an investment".

The Financial Behavior index measures the ability to manage money properly and is given by the sum to 8 questions: "(1) Carefully considers purchases; (2) Pays bills on time; (3) Keeps close watch on personal financial affairs; (4) Sets long term goals

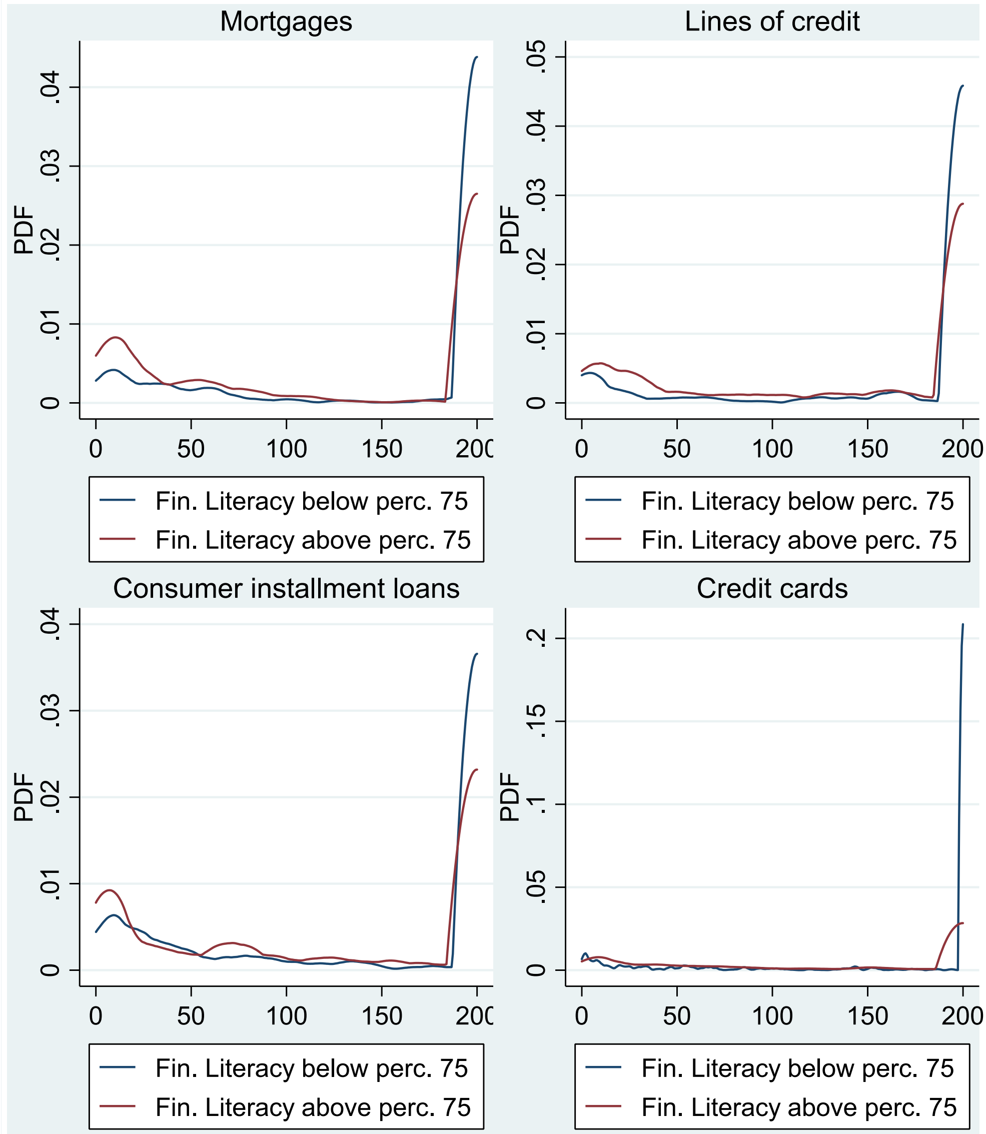

Fig. A.1. Probability density function (pdf) of the absolute proportional differences between the Survey and the Administrative records, according to the financial literacy levels.

Table A.9
Sample balance for the matching regression on the proportional differences.

	Raw	Matched
Resp. is a male	0.48	0.05
Resp. is married	0.25	0.01
Two generations	−0.10	−0.00
Three or more generations	−0.15	0.00
Average INR — income & assets	−0.02	0.01
Rounding rate — income & assets	−0.09	−0.03

Notes: This Table assesses the balance for the computations of the treatment effects, by comparing the means in the raw and balanced datasets. The results correspond to the model estimates that define as treated units those whose FPC financial literacy score is above the 75th percentile of the empirical distribution of this variable. The Table considers the same model specification than in the fourth column of Table 4. Resp. stands for respondent and INR for item non-response. For details on each variable, please refer to Table A.5 in the Appendix.

and strives to achieve them; (5) Responsible and has a household budget; (6) Has saved in the last 12 months using any of these methods (a) checking account, (b) savings account, (c) financial investments and mutual funds, (d) real estate purchases or other properties, (e) family or friends; (7) Do you always stick to your household budget; (8) If you had an emergency spending today, would you be able to make ends meet without asking for a loan or help from family and friends".

The Financial Knowledge index is given as the sum of the correct answers to 8 questions regarding (1) Division, (2) Time value of money, (3) Interest paid on loan, (4) Calculation of interest plus principle, (5) Compound interest, (6) Risk and return, (7) Definition of inflation, (8) Diversification and risk of investment portfolios. These are the basic concepts measured in the literature on financial literacy as a pre-requisite for making sound financial decisions (Lusardi and Mitchell, 2014).

The Financial Search index (or Financial Product Choice index in Atkinson and Messy, 2012) is given by the sum of 2 questions on whether the household has actively chosen any financial product (whether a savings account, investment or loan product) "after gathering some information on financial products" and "after shopping around and using independent information or advice". The question on whether the household has gathered information or used independent advice for the purchase of a

Table A.10
Average treatment effect of financial literacy (FPC fin. literacy score above the percentile 75 or the median) on the proportional differences.

Threshold	ATE	ATE^{+}
Above percentile 75	-23.87^{***}	-23.65^{***}
Above median	-30.31^{***}	-32.03^{***}

Notes: This Table exhibits the average treatment effect of financial literacy on the proportional differences between the Survey and the administrative records. The estimation follows the nearest neighbor matching strategy detailed in Section 3.3. We consider as the treated units the financially literate respondents and the non-treated units as the financially illiterate respondents. To measure financial literacy, we consider the first principal component of our three financial literacy proxies and the categorical variable for the maximum level of education attained by the respondent (FPC financial literacy score). We have two alternative definitions of treated units: (i) those whose FPC financial literacy score is above the 75th percentile of the empirical distribution of this variable; (ii) those households whose FPC financial literacy score is above the median. We include the same demographic, survey and unobservable quality variables that we include in the model specifications in Table 4. The symbol (+) indicates the inclusion of interviewer fixed effects and the exclusion of the 2011 wave, given that the interviewers' information is not available for the year 2011. *** p<0.01, **p<0.05, * p<0.1. Resp. stands for respondent, stud. for studies, and fin. stands for financial. FPC abbreviates first principal component. For details on each variable, please refer to Table A.5 in the Appendix.

financial product was made for 29 financial products. Therefore, the Financial Search Index for each respondent i is given by: $S_i = \max_k 1$ (Respondent i searched for information (whether with same institution or several institutions) on product k) + $\max_h 1$ (Respondent i used independent advice of source h on choosing financial products).

The list of $k = 1, \ldots, 29$ financial products is given by: cash in advance, auto loans with specialized lenders, consumer installment loans from specialized divisions of banks, checks, current accounts, savings accounts, fixed-term deposits, debit cards, voluntary pension plans, pension funds, equities, mutual funds, cooperatives' credit, lines of credit, current and savings accounts, credit with labor unions, retail stores' credit, microcredit, leasing, factoring, mortgages, consumer installment loan, life or home insurance, vehicle insurance, health insurance, credit card, other products.

The list of $h = 1, \ldots, 14$ sources of financial advice correspond to: prior personal experience, advertising or product information provided by the financial institution directly, articles or advertising on the news or magazines, website of the financial institution, online news-advertising or information, radio advertising, professional help provided by your employer, advice from friends or relatives (who do not work for financial entities), advice from friends or relatives who work for financial entities, TV advertising or information, personal contact in-person with executives or representatives of the financial entity, recommendations made by an independent financial adviser, information sent by post mail, information provided by phone.

There is no definite justification for including all the questions in the OECD INFE definition or just a subset of them (Lusardi and Mitchell, 2014; Hung et al., 2020). The first academic studies in the 2000s used measures of financial literacy with just three questions (about compound interest, inflation and risk diversification). Researchers later expanded these questions to form the eight questions of the OECD-INFE Financial Knowledge Index that is used in our article (Lusardi and Mitchell, 2014; Hung et al., 2020). There are no empirical studies of whether adding the other OECD-INFE indexes is a better practice or if it is better to use a simple sum of all the questions available rather than a principal components analysis (Hung et al., 2020). Table A.8, in Appendix, exhibits the correlation matrix among the various financial literacy proxies we consider in this paper.

A.2. Additional tables

See Tables A.1–A.10.

A.3. Additional figures

See Fig. A.1.

References

Abowd, J.M., Stinson, M.H., 2013. Estimating measurement error in annual job earnings: A comparison of survey and administrative data. Rev. Econ. Stat. 95, 1451–1467.

Agarwal, S., Qian, W., Tan, R., 2020. Household Finance. Springer.

Akin, G.G., Aysan, A.F., Ozcelik, S., Yildiran, L., 2012. Credit card satisfaction and financial literacy: Evidence from an emerging market economy. Emerg. Mark. Finance Trade 48, 103–115.

Allen, J., Clark, R., Houde, J.-F., 2019. Search frictions and market power in negotiated-price markets. J. Polit. Econ. 127 (4), 1550–1598.

Alvarez, F., Guiso, L., Lippi, F., 2012. Durable consumption and asset management with transaction and observation costs. Amer. Econ. Rev. 102 (5), 2272–2300.

Alwin, D.F., Zeiser, K., Gensimore, D., 2014. Reliability of self-reports of financial data in surveys: results from the health and retirement study. Sociol. Methods Res. 43 (1), 98–136.

Ameriks, J., Caplin, A., Lee, M., Shapiro, M.D., Tonetti, C., 2015. The wealth of wealthholders. Working Papers No. 2972, National Bureau of Economic Research.

Atkinson, A., Messy, F., 2011. Assessing financial literacy in 12 countries: An OECD/INFE international pilot exercise. J. Pension Econ. Finance 10 (4), 657–665.

Atkinson, A., Messy, F., 2012. Measuring financial literacy: Results of the OECD/international network on financial education (INFE) pilot study. OECD Working Papers on Finance No. 15, OECD Publishing, Paris.

Badarinza, C., Campbell, J.Y., Ramadorai, T., 2016. International comparative household finance. Annu. Rev. Econ. 8, 111–144.

Baker, S.R., Kueng, L., Meyer, S., Pagel, M., 2021. Consumption imputation errors in administrative data. Rev. Financ. Stud. Forthcoming.

Banco Central de Chile, 2018. Encuesta financiera de hogares 2017: Metodología.

Barceló, C., 2006. Imputation of the 2002 wave of the spanish survey of household finances (EFF). Occasional Paper No. 0603, Bank of Spain.

Beck, T., Brown, M., 2015. Foreign bank ownership and household credit. J. Financial Intermediation 24 (4), 466–486.

Beck, T., Lu, L., Yang, R., 2015. Finance and growth for microenterprises: Evidence from rural China. World Dev. 67, 38–56.

Behrman, J.R., Mitchell, O.S., Soo, C.K., Bravo, D., 2012. How financial literacy affects household wealth accumulation. Amer. Econ. Rev. 102 (3), 300–304.

Bhandari, A., Birinci, S., McGrattan, E.R., See, K., 2020. What do survey data tell us about US businesses? Am. Econ. Rev.: Insights 2 (4), 443–458.

Blattman, C., Jamison, J., Koroknay-Palicz, T., Rodrigues, K., Sheridan, M., 2016. Measuring the measurement error: A method to qualitatively validate survey data. J. Dev. Econ. 120, 99–112.

Bound, J., Krueger, A.B., 1991. The extent of measurement error in longitudinal earnings data: Do two wrongs make a right?. J. Labor Econ. 9 (1), 1–24.

Bover, O., Casado, J.M., Costa, S., Caju, P.D., McCarthy, Y., Sierminska, E., Tzamourani, P., Villanueva, E., Zavadil, T., 2016. The distribution of debt across Euro-Area countries: The role of individual characteristics, institutions, and credit conditions. Int. J. Central Bank. 12 (2), 71–128.

Brown, M., Grigsby, J., Van Der Klaauw, W., Wen, J., Zafar, B., 2016. Financial education and the debt behavior of the young. Rev. Financ. Stud. 29 (9), 2490–2522.

Brown, M., Haughwout, A., Lee, D., van der Klaauw, W., 2015. Do we know what we owe? Consumer debt as reported by borrowers and lenders. Econ. Policy Rev. 21 (1), 19–44.

Browning, M., Crossley, T.F., Winter, J., 2014. The measurement of household consumption expenditures. Annu. Rev. Econ. 6 (1), 475–501.

Christelis, D., Georgarakos, D., Haliassos, M., 2013. Differences in portfolios across countries: Economic environment versus household characteristics. Rev. Econ. Stat. 95 (1), 220–236.

Cull, R., Gan, L., Gao, N., Xu, L.C., 2019. Dual credit markets and household usage to finance: Evidence from a representative Chinese household survey. Oxf. Bull. Econ. Stat. 81 (6), 1280–1317.

Cunha, F., Heckman, J., Navarro, S., 2005. Separating uncertainty from heterogeneity in life cycle earnings. Oxf. Econ. Pap. 57 (2), 191–261.

Davis, S.J., Faberman, R.J., Haltiwanger, J., 2006. The flow approach to labor markets: New data sources and micro-macro links. J. Econ. Perspect. 20 (3), 3–26.

Demirguc-Kunt, A., Klapper, L., Singer, D., Ansar, S., Hess, J.R., 2018. The Global Findex Database 2017: Measuring Financial Inclusion and the Fintech Revolution. World Bank Publications.

Disney, R., Gathergood, J., 2013. Financial literacy and consumer credit portfolios. J. Bank. Financ. 37 (7), 2246–2254.
Eggleston, J., Reeder, L., 2018. Does encouraging record use for financial assets improve data accuracy? Evidence from administrative data. Public Opin. Q. 82 (4), 686–706.
Fernandes, D., Lynch, J.G., Netemeyer, R.G., 2014. Financial literacy, financial education, and downstream financial behaviors. Manag. Sci. 60 (8), 1861–1883.
Fesseau, F.W., Mattonetti, M., 2013. A cross-country comparison of household income, consumption and wealth between micro sources and national accounts aggregates. OECD Statistics Working Papers No. 2013/03, OECD Publishing, Paris.
Fujiki, H., 2020a. Cash demand and financial literacy: A case study using Japanese survey data. Japan World Econ. (ISSN: 0922-1425) 54, 100998.
Fujiki, H., 2020b. The use of noncash payment methods for regular payments and the household demand for cash: Evidence from Japan. Jpn. Econ. Rev. 71 (4), 719–765.
Fujiki, H., Tanaka, M., 2018. How do we choose to pay using evolving retail payment technologies? evidence from Japan. J. Jpn. Int. Econ. (ISSN: 0889-1583) 49, 85–99.
Gideon, M., Helppie-McFall, B., Hsu, J.W., 2017. Heaping at round numbers on financial questions: The role of satisficing. Survey Res. Methods 11 (2), 189–214.
Gomes, F., Haliassos, M., Ramadorai, T., 2021. Household finance. Journal of Economic Literature 59 (3), 919–1000.
Hastings, J.S., Madrian, B.C., Skimmyhorn, W.L., 2013. Financial literacy, financial education, and economic outcomes. Annu. Rev. Econ. 5 (1), 347–373.
Hung, A., Parker, A.M., Yoong, J., 2020. Defining and measuring financial literacy. Working Paper Series WR-708, RAND.
Huston, S.J., Measuring financial literacy. J. Consumer Aff. 44 (2), 296–316.
Hyslop, D.R., Townsend, W., 2020. Earnings dynamics and measurement error in matched survey and administrative data. J. Bus. Econom. Statist. 38 (2), 457–469.
Kaiser, T., Lusardi, A., Menkhoff, L., Urban, C., 2021. Financial education affects financial knowledge and downstream behaviors. J. Financ. Econ..
Kapteyn, A., Ypma, J.Y., 2007. Measurement error and misclassification: A comparison of survey and administrative data. J. Labor Econ. 25 (3), 513–551.
Karlan, D., Zinman, J., 2008. Lying about borrowing. J. Eur. Econom. Assoc. 6 (2–3), 510–521.
Kennickell, A.B., 2017. Wealth measurement in the survey of consumer finances: Methodology and directions for future research. Stat. J. IAOS 33 (1), 23–39.
Kim, J., Waite, L.J., 2016. Complex households and the distribution of multiple resources in later life: Findings from a national survey. Res. Aging 38 (2), 150–177.
Klapper, L., Lusardi, A., Panos, G.A., 2013. Financial literacy and its consequences: Evidence from Russia during the financial crisis. J. Bank. Financ. 37 (10), 3904–3923.
Lewbel, A., 2012. Using heteroscedasticity to identify and estimate mismeasured and endogenous regressor models. J. Bus. Econom. Statist. 30 (1), 67–80.
Lusardi, A., Mitchell, O.S., 2011. Financial literacy and retirement planning in the United States. J. Pension Econ. Finance 10 (4), 509–525.
Lusardi, A., Mitchell, O.S., 2014. The economic importance of financial literacy: Theory and evidence. J. Econ. Lit. 52 (1), 5–44.
Madeira, C., 2021. The potential impact of financial portability measures on mortgage refinancing: evidence from chile. Journal of International Money and Finance 117, 102455.
Madeira, C., Margaretic, P., Martínez, F., Roje, P., 2022. Assessing the quality of self-reported financial information. Journal of Survey Statistics and Methodology.
Maynes, E.S., 1968. Minimizing response errors in financial data: The possibilities. J. Amer. Statist. Assoc. 63 (321), 214–227.
Meriküll, J., Room, T., 2020. Stress tests of the household sector using microdata from survey and administrative sources. Int. J. Central Bank. 62.
Mittag, N., 2019. Correcting for misreporting of government benefits. Am. Econ. J.: Econ. Policy 11 (2), 142–164.
Neri, A., Monteduro, M.T., 2013. The housing wealth of Italian households: a comparison of administrative and survey data. In: Bank of Italy, Economic Research and International Relations Area.
OECD, 2020. OECD/INFE 2020 international survey of adult financial literacy. Technical Report, OECD.
Paulus, A., 2015. Tax evasion and measurement error: An econometric analysis of survey data linked with tax records. tech. rep., ISER Working Paper Series.
Pedace, R., Bates, N., 2000. Using administrative records to assess earnings reporting error in the survey of income and program participation. J. Econ. Soc. Measur. 26, 173–192.
Ponce, A., Seira, E., Zamarripa, G., 2017. Borrowing on the wrong credit card? Evidence from Mexico. Amer. Econ. Rev. 107 (4), 1335–1361.
Rencher, A., Christensen, W., 2012. Methods of Multivariate Analysis, third ed. Wiley.
Thoemmes, F.J., Kim, E.S., 2011. A systematic review of propensity score methods in the social sciences. Multivar. Behav. Res. 46 (1), 90–118.
Törnqvist, L., Vartia, P., Vartia, Y.O., 1985. How should relative changes be measured?. Amer. Statist. 39 (1), 43–46.
Tufano, P., 2009. Consumer finance. Ann. Rev. Financial Econ. 1, 227–247.
Woodward, S.E., Hall, R.E., 2012. Diagnosing consumer confusion and sub-optimal shopping effort: Theory and mortgage-market evidence. Amer. Econ. Rev. 102 (7), 3249–3276.
Zait, A., Bertea, P.E., 2014. Financial literacy – conceptual definition and proposed approach for a measurement instrument. J. Account. Manag. 4 (3).
Zakrison, T., Austin, P., McCredie, V., 2018. A systematic review of propensity score methods in the acute care surgery literature: Avoiding the pitfalls and proposing a set of reporting guidelines. Eur. J. Trauma Emerg. Surg. 44 (3), 385–395.
Zinman, J., 2009. Where is the missing credit card debt? Clues and implications. Rev. Income Wealth 55 (2), 249–265.