Policy-effective Financial Knowledge and Attitude Factors

Abstract

In this paper, we consolidate two objectives of the financial inclusion literature: producing meaningful measures of financial knowledge and financial attitudes and providing guidance to policymakers in cost-benefit analysis for the comparison of financial education interventions. We call them policy-effective factors. For this, we estimate a system of equations in which the dependent binary variables represent financial behavior and explanatory variables include knowledge and attitude variables and controls. Using Brazilian data from OECD/INFE survey 2015, we find one knowledge factor and two attitude factors that help predict behavior outcomes.

Keywords: financial inclusion, financial literacy, financial knowledge

JEL Classification: D83, G29, A20, D12, D14, I28

1. Introduction

It is an established fact in literature that financial development and economic development go hand in hand (see, for example, Levine, 1997). In order to reap the benefits from financial markets, individuals need to have access to financial products and to be able to use them in a way that enhances their choice set and improves their expected outcomes. They need, for instance, a set of skills to use credit properly to smooth shocks instead of becoming prey of overconsumption. This is why countries are recently devoting resources to measure and improve financial knowledge and attitudes of the population.

In spite of the ongoing significant progress in the field, some questions remain not fully answered. What are most relevant questions to ask in surveys about financial knowledge and financial attitudes? How to combine them in indexes that allow analysts to measure improvement along time and compare populations? At the same time, how to select the right targets for financial educations programs? In this paper, we argue that financial behavior outcomes should play the main role in providing guidance for this research, since they are the bridge to improved welfare.

We propose to address these themes with a new methodology that estimates a system of equations with behavioral outcomes related to financial inclusion as a function of knowledge, attitude and control variables. Our first contribution is to generate a framework to aggregate survey questions into outcome-relevant indexes. This differs greatly from the techniques that the literature has used so far, as we discuss in section 2.

The second contribution, relevant for financial education policy, is simplifying comparison between the benefits that may be reaped from enhancing different aspects of population knowledge (or attitude). We argue that this may be achieved by using the policy-effective factors that we build as intermediate policy targets.

A third, more limited, contribution we offer concerns the search econometric for instruments. As we discuss in the next section, the literature has struggled to find adequate econometric instruments to deal with endogeneity in estimations that use behavioral outcomes and knowledge or attitude explanatory variables. We take advantage of the system structure to select instruments from the set of controls, and show that they have similar performance than most additional questions or natural experiments used in the literature.

Bherman et al (2012) understand the term financial literacy as "the ability to process economic information and make informed decisions about household finances". A growing line of papers[1] has structured the study of financial literacy and its relationship with financial behavior in frameworks that fit the Knowledge-Attitude-Behavior (KAB) approach. Schrader and Lawless (2004) explain in detail the KAB framework. Knowledge refers to all information that

[1] For example, van Rooij et al. (2011) and Bachmann & Hens (2015). Lusardi & Mitchell (2014) includes a survey.

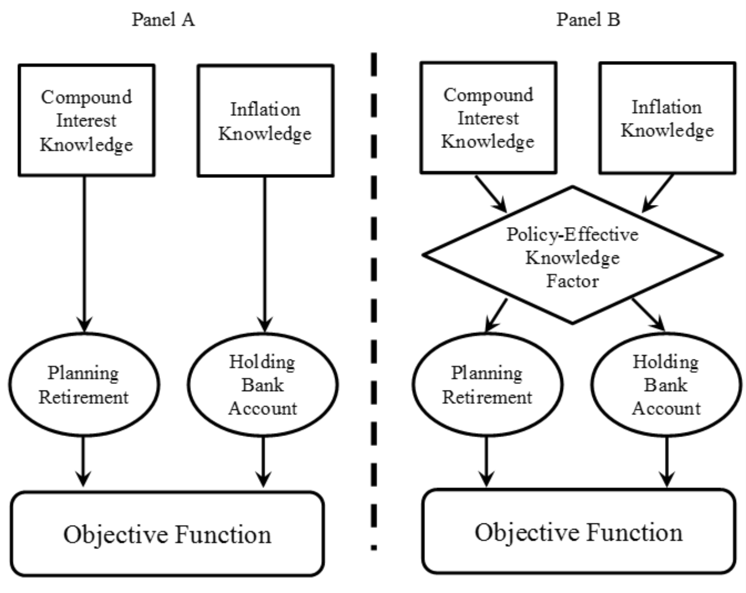
individuals have. Attitudes (which seem to be the most complex to define) are generally understood as concerning how people feel (emotional), although the authors point out that they may include some aspects relating to knowledge (beliefs) and to behavior (predispositions)[2]. Finally, behaviors are observable actions. The authors find in the literature that the relationship between knowledge and behavior may be reciprocal and dynamic, but it seems that the literature generally understands one affecting the other through attitudes.

Generally, policymakers expect changes induced though financial education initiatives to be able to affect financial knowledge, which in turn, should affect attitudes and behavior. This fact divides the problem into two parts: linking educational actions to knowledge, and liking knowledge to all the rest. This paper focuses on the latter, and thus, assumes it is possible to affect knowledge[3].

Consider the simplified motivational example of a policymaker with two objectives regarding financial behavior: she would like people to have some sort of bank account and to plan for retirement. She is aware of two abilities that contribute for people to behave that way: being able to perform compound interest calculations and knowing that inflation affects the purchasing power of savings. These are tools to obtain behavioral goals. Since resources are scarce, the policymaker is trying to decide which of these two abilities will be targeted by a financial education program.

Some different configurations may arise from this example. First, as depicted in Panel A of Figure 1, it is possible that, say, performing compound interest calculations increases the probability that an individual plans retirement while being innocuous for the probability of holding a bank account, whereas the inverse happens for knowing about inflation. Then, there is a tradeoff between goals, and the choice of the tool will depend upon which behavioral objective is regarded as more important. Defining that is very complex, since it should reflect preferences.

Figure 1 – Comparing Benefit-Cost analysis both settings



[2] Hung, Parker & Yoong (2009) draw attention to the fact that attitudes are derived, at least in part, from preferences.
[3] See Lusardi & Mitchell (2014) about papers on interventions and their results.

Yet, as depicted in Panel B of Figure 1, the situation is quite different if both tools affect the objectives in a "similar" way. Then, there is no tradeoff between objectives and the decisions hinges only on comparing the tools effectiveness with their cost. If being able to perform compound interest rate calculation increased the probability of individuals having a bank account and of planning for retirement twice as much as knowing the consequences of inflation, and teaching both to the population costs the same, the policymaker would choose to teach compound interest.

In this paper, we propose a way to test in data[4] which of these two situations is relevant for the setting. Since many of the goals in financial behavior are related, it makes sense that at least some tools have "similar" impacts on many of them, and this simplifies policy choice a great deal.

This discussion is also relevant for the definition of indexes that measure financial knowledge or financially desirable attitudes. If we have available the survey answers for a set of questions regarding financial knowledge, the simplest and *ex ante* most reasonable way to compute a score by summing the number or right answers. We do this in the next section. However, if we find out that the "compound interest" question has twice the impact on policy goals of the "inflation" question, we should give the former a weight twice as large as the latter, in order to obtain an index that is more meaningful in predicting the financial behavioral outcomes.

We estimate knowledge and attitudes factors that explain the most out of the financial behavior outcomes[5]. We call these policy-effective factors. This is a very different approach than using traditional factor analysis, which relies on the communality of variable groups, whereas the methodology we propose combines variables that contribute in a similar way to outcomes, without requiring them to be correlated among themselves.

The next section presents the most relevant literature regarding financial knowledge measures. Section 3 formalizes a policymaker model in order to show the gains from using policy-effective factors and how to estimate them. In section 4, we explain the Brazilian dataset, make some international comparisons and explore it with traditional factor analysis. Section 5 presents the empirical results of the new technique and section 6 addresses endogeneity. Section 7 concludes.

2. Literature

Lusardi & Mitchell (2014) provide a comprehensive survey of the literature concerning several aspects of financial literacy. Our work relates to the literature that investigates whether high financial knowledge and good financial attitude measures predict desirable behavior outcomes. In short, several studies document that the level of financial

[4] A drawback, prevalent in most of literature relating financial knowledge (or literacy) to inclusion, is endogeneity. We come back to that point ahead.

[5] A further gain comes from the fact that one may be concerned about a certain subject being overrepresented in surveys, when there are potentially similar questions. If the answers to two questions are highly correlated, naturally the econometric estimation of equations explaining outcomes requires the exclusion of one.

knowledge relates to holding precautionary savings, planning for retirement, using less costly financing and avoiding fees.

In this section, we focus another aspect: the literature that combined survey questions into knowledge and attitude measures. Two direct ways of combining the answers to financial knowledge questions are commonly used in the literature. First, authors have used the definition of a dummy variable that takes on the value of one if the individual gets all the questions right and zero otherwise. This approach is taken, for example, in Lusardi and Mitchell (2011)[6]. Since this is generally applied on a short list of questions (the first three in Lusardi & Mitchell (2008) have become classics), which address the pillars of financial knowledge, it makes sense to give 0 to anyone who is unable to get all questions right. The main caveat is that while everyone being assigned 1 had actually the same answer profile, there is heterogeneity in the group getting 0, which is lost by the measure.

This calls for the other widely applied method of turning answer profiles into scores: giving 1 point for every questions properly answered. Atkinson and Messy (2012) and Finke, Howe and Huston (2011) compute measures based on this sort of score[7]. This approach has the merit of preserving heterogeneity and being more appealing to surveys with longer lists of questions. If you ask ten questions, you probably would not want to group people who erred just one question together with those that got all wrong. The problem with this way of computing scores is that all questions get the same weight. Then, everyone that gets 4 right answers is attributed the same score, no matter which subset of the financial knowledge body the subject is signaling to know, and it may be hard to believe that all of them matter the same. This is clear in Lusardi and Mitchell (2011), who compare this sort of score with including dummies for each question. Still, it is a simple direct and transparent way of computing a score.

On the other hand, although this path has been less frequent, some studies used factor analysis as way to group questions that are correlated, for example Lusardi & Mitchell (2007b) and van Rooij et al (2011)[8]. This is useful since it avoids arbitrarily summing points and, at the same time, account for the answers as possibly resulting from different pieces of underlying knowledge. However, this approach emphasizes commonality among variables, and this may be a drawback if we are interested in behavioral outcomes, because if all variables are highly correlated (which is good as long as factor analysis is concerned), it may mean that other uncorrelated dimension might add discriminatory and explanatory power. Behrman et al.(2012) make an interesting progress on this issue, proposing a measure of financial knowledge based on a two-step procedure: the first generates weights that punish more the individuals who get wrong something that most of other get right, while the second uses principal components analysis to take into account correlation between questions. We propose that it is more useful to have a measurement of financial knowledge that can combine different (potentially uncorrelated) signals of knowledge and weight them according to their importance in predicting behavior.

[6] Check Lusardi & Mitchell (2014), table 2, for a list of papers that employed this approach around the world.
[7] Hung, Parker & Yoong (2009) provide a table including several papers and the scales they used.
[8] Huston, Finke & Smith (2012) use this approach to compute a financial sophistication proxy.

3. Model and Econometric Implementation

3.1. Model

Assume a policymaker with a vector of behavioral outcomes $[y_1, y_2, \dots, y_n]$ which affect the objective function $Y = f(y_1, y_2, \dots, y_n)$.

Now, imagine that the y_i are affected by policy variables $[x_1, x_2, \dots, x_m]$ in the following manner (for simplicity, we temporarily ignore controls):

$$\begin{aligned} y_1 &= g_1(a_{11}x_1 + a_{12}x_2 + \cdots + a_{1m}x_m) + \varepsilon_1 \\ y_2 &= g_2(a_{21}x_1 + a_{22}x_2 + \cdots + a_{2m}x_m) + \varepsilon_2 \\ &\vdots \\ y_n &= g_n(a_{n1}x_1 + a_{n2}x_2 + \cdots + a_{1m}x_m) + \varepsilon_n \end{aligned} \tag{1}$$

where, $g_i(\cdot)$ are possibly nonlinear functions and ε_i are zero mean random shocks, which may be correlated to one another but are independent of the x_j.

Finally, assume that increasing x_j by one unit has a cost p_j and the policymaker's budget is limited to amount B.

Assuming regularity conditions, first order conditions of the policymaker's problem are given by:

$$\sum_{i=1}^{n} \frac{\partial Y(\cdot)}{\partial y_i}\frac{\partial y_i}{\partial x_j} - \lambda p_j = 0$$

$$\therefore \sum_{i=1}^{n} \frac{\partial Y(\cdot)}{\partial y_i} g_i'(\cdot)a_{ij} - \lambda p_j = 0$$

where $j = 1, \dots m$.

While comparing two instruments, this implies a no arbitrage condition given by:

$$\frac{\sum_{i=1}^{n}\left(\frac{\partial Y(\cdot)}{\partial y_i} g_i'(\cdot)a_{ij}\right)}{\sum_{i=1}^{n}\left(\frac{\partial Y(\cdot)}{\partial y_i} g_i'(\cdot)a_{ik}\right)} = \frac{p_j}{p_k} \tag{2}$$

The implementation of such solution in a real context requires full knowledge of function $Y(\cdot)$ and of the specific impacts of each x_j on each y_i. Thus, from a surface in $\mathbb{R}^m$, the policymaker needs to find the best attainable outcome in $\mathbb{R}^n$.

But what if objectives happened to be somewhat aligned? In particular, instead of (1), assume:

$$\begin{aligned} y_1 &= g_1(\gamma_1(c_1x_1 + c_2x_2 + \cdots + c_mx_m)) + \varepsilon_1 \\ y_2 &= g_2(\gamma_2(c_1x_1 + c_2x_2 + \cdots + c_mx_m)) + \varepsilon_2 \\ &\vdots \\ y_n &= g_n(\gamma_n(c_1x_1 + c_2x_2 + \cdots + c_mx_m)) + \varepsilon_n \end{aligned} \tag{3}$$

Then, the first order condition implies:

$$\frac{\sum_{i=1}^{n}\left(\frac{\partial Y(\cdot)}{\partial y_i} g_i'(\cdot)\gamma_i\right) a_j}{\sum_{i=1}^{n}\left(\frac{\partial Y(\cdot)}{\partial y_i} g_i'(\cdot)\gamma_i\right) a_k} = \frac{p_j}{p_k}$$

$$\therefore\ \frac{a_j}{a_k} = \frac{p_j}{p_k} \qquad (4)$$

Hence, given that (3) is a restricted version of (1), if such restriction of the problem is not rejected by data, it is useful to employ this latter version, since (4) is much simpler than (2). It dispenses with the full knowledge of $Y(\cdot)$ and, at the time of decision making, all that matters is how each x_j affects the intermediate target or, as we call it, policy-effective factor:

$$f = [\, c_1x_1 +\ c_2x_2 + \cdots +\ c_mx_m] \qquad (5)$$

3.2. Econometric Implementation

Since in our dataset the behavioral outcomes are binary, we model outcomes as coming from a logistic distribution[9], thus, each equation in (1) takes the form:

$$E(y_i/X) = g_i(X) = g(X\beta_i) = \frac{1}{1+e^{-X\beta_i}} \qquad (6)$$

$$X\beta_i = a_{i0} + D\beta_{Di} + K\beta_{ki} + A\beta_{ai}$$

where X represents the matrix of regressors, which we break down into a vector of ones, a matrix of demographic controls (D), a matrix of knowledge variables (K) and a matrix of attitude variables (A).

We estimate a system with $i = 1, \ldots, 12$ using nonlinear SUR, with robust standard errors. This allows us to implement directly restriction Wald tests to verify if the coefficients of a knowledge (or attitude) variable are proportional the coefficients of another variable along the equations of the system, i.e. if we can write (1) as (3). In case the hypothesis of proportional coefficients is not rejected, both variables generate a factor. Then the inclusion of other variables in the factor is tested along the same lines.

Coefficients that multiply variables inside the factors are estimated using all equations, while a coefficient multiplying a factor is unrestricted in each equation. Identification requires fixing one of these coefficients. We choose to set the coefficient of each factor in the first equation equal to one. At each step the inclusion of all remaining variables in the factors are tested, and we select the next variable to include using two criterions: we give priority to variables that are significant in a larger number of equations and that result in not rejection of the inclusion hypothesis with higher p-value.

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[9] We choose this distribution because it yields a closed form cdf (unlike the Gaussian distribution), while it keeps generally desirable properties like not producing estimated probabilities outside the [0,1] interval and a decreasing pdf as the argument moves away from the mean.

In terms of equations, consider system (6) in the current application and, assume, in particular, that we are building a knowledge factor. Two knowledge variables were already determined to belong in it, while other two are still candidates. Then, the system would look like:

$$y_1 = g(a_{10} + D\beta_{D1} + 1[c_1k_1 + c_2k_2] + a_{13}k_3 + a_{14}k_4 + A\beta_{a1}) + \varepsilon_1$$
$$y_2 = g(a_{20} + D\beta_{D2} + \gamma_2[c_1k_1 + c_2k_2] + a_{23}k_3 + a_{24}k_4 + A\beta_{a1}) + \varepsilon_2 \qquad (7)$$
$$\vdots$$
$$y_n = g(a_{n0} + D\beta_{Dn} + \gamma_n[c_1k_1 + c_2k_2] + a_{n3}k_3 + a_{n4}k_4 + A\beta_{a1}) + \varepsilon_n$$

At this point, we would want to test if k_3 may be included in the knowledge factor currently formed by $[c_1k_1 + c_2k_2]$, and the null hypothesis would be:

$$H_0: \frac{1}{\gamma_2} = \frac{a_{13}}{a_{23}} \; ; \; \frac{1}{\gamma_3} = \frac{a_{13}}{a_{33}} \; ; \ldots ; \; \frac{1}{\gamma_n} = \frac{a_{13}}{a_{n3}} \qquad (7)$$

Since the system is quite large (fully unrestricted estimation would mean too many parameters) we employ stepwise procedure. First, we include only controls, and exclude the ones that are not significant at 10% confidence interval. Then we include knowledge variables and specify the knowledge factors, excluding them from the equations in which they are not significant. Then we proceed in the same way with attitude variables. Finally, we test the inclusion of knowledge and attitude variables that are not included in factors. After each inclusion of a variable in a factor, the significance of the modified factor is tested again in all equations, and the whole system is cleaned of not significant variables.

4. Data and the Brazilian Landscape

Adequately measuring financial knowledge is complex issue. Given that most measurements are implemented using surveys and asking people what they know and how they feel about statements, not only deciding which aspects to try to assess, but also the wording of questions (see van Rooij et al., 2011) and how the subjects are approached may dramatically influence the outcomes. We start our empirical application from OECD/INFE survey, which is already the result of substantial research in relevance of questions and design, and we estimate a nonlinear equation system model, using the 2015 application for Brazil.

The OECD/INFE survey provides a framework to survey financial capabilities, and its use in several countries is of the utmost importance, since it is building a large set of internationally comparable data. In 2015, following a directive from INFE’s technical committee, OECD performed a second international comparison. The instrument was used in 30 countries in order to gather information and guide policy regarding the theme, including Brazil for the first time. In Brazil, the survey was conducted by a partnership among Banco Central do Brasil, Serasa Experian and IBOPE inteligência. A sample of 2.002 individuals, representative of the Brazilian population older than 16 years was surveyed. Sample representativeness was obtained using a three-stage stratification by conglomerate. This makes the sample self-weighting.

The OCDE/INFE survey comprises 40 questions, out of which 31 constitute a minimum mandatory core to be applied by all countries that participate in this second international comparison[10]. The Brazilian version includes, additionally to this core, other 16 questions intended, on the one hand, to assess the use credit instruments and to qualify this use according to the financial health of the households and, on the other hand, to complement information about savings and financial knowledge considered relevant at the national level. Nine of these questions allowed us to identify more precisely financed goods and knowledge of the surveyed individuals.

Generally speaking, the distribution according to gender, income level, federation unit and municipality of residence size are adherent to data obtained from the 2010 census, thus confirming the representativeness of the sample for the Brazilian population. When the age dimension is considered, the sample results are close to the census data, except for the most extreme groups: the group of 16 and 17-year-olds is slightly subsampled (they represent only 1% of the sample while the participation in Brazilian population is 4.8% in the corresponding group), while the group aged 55 or more have a sample participation 2.8% above the one observed in the 2010 census (20.4%). Finally, in what concerns education, the sample is slightly more educated than the population, featuring a participation of only 33.2% of individuals with no formal education, while in Brazilian population this figure is of 45.2%. On the other hand, the group with complete secondary school represents 38.6% of the sample, against 26.4% in the 2010 census data.

The behavior variables comprise information regarding saving habits, whether the family keeps a budget, retirement planning and resilience to unexpected shocks, in addition to the use of financial products. It interesting to note that when individuals were directly asked if they save, approximately one third of them answered yes. This number rose to 43.9%[11] when this question was asked so as to explicitly account for savings in the financial system and also for alternative strategies (e.g. keeping cash at home, having money kept by a relative, partaking in informal saving groups, storing goods, etc.). The information about resilience to shocks seems to confirm the one about savings obtained by the direct question. This may imply that alternative saving strategies are smaller than monthly income or present some sort of illiquidity. Only 44% of the surveyed individuals claim to monitor household finances using a budget. As for retirement planning, in Brazil formal employees contribute compulsorily to the official social security program. When we exclude these, only 35.8% of the surveyed individuals spontaneously plan for retirement. Finally, credit cards are the product that reached the widest adoption in surveyed individuals (45%)[12], followed by credit given by retailers to their customers (23.4%) and savings accounts (20.3%).

[10] More detailed information about the OCDE / INFE survey can be found in INFE (2015).
[11] Obtained from the use of at least one of the instruments.
[12] We comment some more about the credit card market in Brazil in section 6.

Turning to knowledge variables, the OECD/INFE survey features a question asking the individual to assess his own level of financial knowledge and other 8 questions regarding subjects from basic arithmetic to notions of inflation, risk and return and investment diversification. In Brazil, in addition to these, other 4 questions about knowledge were included, aiming to evaluate daily life issues, like notions of consumer rights and current level of inflation (economic outlook).

In order to build a simple indicator for the knowledge level, we attribute a point for each right answer, thus generation a score that may vary between 0 a 12. Since we seek to understand the relationship between behavior and knowledge, for each financial behavior variable we break the sample in two (whether the behavior is reported to happen or not) and perform t tests to compare the average of the knowledge score between these groups. Except for the use of retailer credit and for saving out of the financial system, always the group that uses the financial product in question or presents a desirable financial behavior (making a household budget, being resilient to unexpected shocks and planning for retirement) presented a higher score than the one obtained by the other group, in which these characteristics are absent. Although these results cannot identify causality, they point towards the existence of a relationship between financial behavior and financial knowledge of these individuals.

Table 4.1 – Comparison between the knowledge score and behavior variables

Behavior variables	Not	Yes	significance
Use of credit cards	7.4	8.2	< 0.001
Use of checking account overdraft	7.7	8.3	< 0.001
Use of payroll consigned credit (wage collateralized)	7.8	8.2	0.01
Use of general purpose financial system loans	7.7	8.1	0.011
Use of retailer credit	7.7	7.9	0.202
Use of vehicle financing	7.7	8.5	< 0.001
Use of savings account	7.6	8.4	< 0.001
Making a household budget	7.6	8.0	< 0.001
Saving	7.6	8.3	< 0.001
Saving in the financial system	7.8	7.9	0.285
Saving out of the financial system	7.6	8.4	< 0.001
Prepared to face and unexpected shock without resorting to borrowing	7.6	8.3	< 0.001
Plans for retirement	7.7	7.9	0.006

Regarding attitude variables, in order to make comparisons between questions more direct, we adopted for each of them a score ranging between 1 and 5, increasing with the desirability of the answer. We employ factor analysis to identify set of constructs that may underlie sets of variables. Results are shown in table 4.2. Even though this analysis does not present adequate results, given the small portion of variability explained by the factors and the low communality of many variables (total variance explained by the set of factor is only 68%, with a Cronbach's Alpha of 63%, indicating that the variables do not measure a common underlying factor), it allows us to identify some groupings. The first one, composed of items 3, 7,8,9,10,15 and 16 of question 1B seems to relate to financial management, while items 1,2,6,11 and 14 share the common idea of concern with the current situation as opposed to the future (carpe diem). Items 12, 13 and 19 reveal an underlying factor of planning ability. Items 4 and 5 seem to convey the idea of appearance / social status and items 17, 18 and question 15 reveal the concern with the financial situation. It is useful to have these groups for comparison. As we show, the technique we propose in this paper groups variables in a very different fashion. Detailed tables containing all descriptive statistics are available upon request.

Table 4.2 – Attitude Variables Factorial Analysis

Attitude variable	Factors					Initial communality
	1	2	3	4	5	
Q1B_10) Before I buy something I carefully consider whether I can afford it	0.762	-0.007	0.038	0.139	0.095	0.611
Q1B_16) I usually feel worried about the payment of common everyday expenditure	-0.759	0.094	0.020	-0.080	0.136	0.611
Q1B_7) I pay my bills on time	0.693	0.028	0.179	0.063	0.327	0.623
Q1B_8) I keep a close personal watch on my financial affairs	0.671	0.103	0.265	-0.004	0.376	0.672
Q1B_9) I talk about financial decisions with other people in my family (e.g. spouse, brothers, parents, children)	0.576	0.102	0.238	-0.047	-0.193	0.438
Q1B_3) In general, I feel capable of managing my personal finances by myself	0.564	-0.106	0.130	-0.053	0.241	0.407
Q1B_15) My financial situation limits my capacity of doing things that are important to me.	-0.528	0.327	0.102	0.041	0.204	0.440
Q1B_14) Money is there to be spent	-0.144	0.695	-0.114	-0.079	0.006	0.524
Q1B_11) I tend to live for today and let tomorrow take care of itself	0.063	0.664	-0.207	-0.059	0.004	0.491
Q1B_1) I find it more satisfying to spend money than to save it for the long term	-0.077	0.638	0.135	0.316	-0.110	0.543
Q1B_2) I prefer to pay for a purchase in instalments than to wait until I have the money to pay for it upfront.	-0.041	0.532	0.057	0.184	0.134	0.340
Q1B_6) I tend to shop in an immediate and spontaneous way, without thinking a lot	0.093	0.483	-0.106	0.427	0.031	0.437
Q1B_12) I am prepared to risk some of my own money when saving or making an investment	0.019	-0.123	0.753	-0.063	-0.020	0.586
Q1B_13) I set long term financial goals and strive to achieve them	0.308	-0.100	0.656	0.102	0.016	0.546
Q1B_19) I am confident on my plans for retirement	0.237	0.014	0.465	-0.202	0.372	0.452
Q1B_5) When I buy something, I generally choose a brand that my friends/relatives will approve of.	0.163	0.035	-0.176	0.748	0.085	0.625
Q1B_4) I admire people who own goods, like expensive clothes or luxury cars	-0.051	0.154	0.077	0.722	0.031	0.555
Q.15) How would you rate your level of financial stress?	-0.007	-0.070	0.063	0.045	0.626	0.403
Q1B_17) I have too much debt right now	0.082	0.232	-0.139	0.287	0.602	0.525
Q1B_18) I am satisfied with my present financial situation	0.116	0.079	0.500	-0.216	0.525	0.592

5. Results

We present the results of applying our technique to the Brazilian OECD/INFE dataset divided accordingly to our main two contributions. In subsection 5.1 we display the composition of the knowledge and both the attitude factors that we identify in the data. We are interested in them as financial knowledge and attitude measurements. We also explore the distribution of these factors along controls that are widely used in the literature.

In section 5.2 we show the coefficients that multiply the factors in each equation, which contribute in analyzing the relationship between the financial knowledge and attitude factors and the behavioral outcomes.

5.1. Factors

Again, we draw attention to the fact that we reverse the scale of some explanatory variables in order to make their values increase as they assume more "desirable" outcomes. This is meant only to make interpretation more direct. Tables 5.1.1 through 5.1.3 present the coefficients in the policy-effective factors, i.e., the c_j in equation (5). We identify one factor for knowledge and two factors for attitudes.

Table 5.1.1 – Questions entering the Financial Knowledge Factor

Question	Value assigned	Coefficient (Std. Dev.)	OECD survey
Suppose 3 friends win together R$1500 in a lottery. If they decide to share the money equally, how much does each one get? (3 alternatives or not know)	dummy =1 if right	0.9841652**** (0.2397367)	Yes
A good way to control monthly expenditure is to make a budget. (True or false)	dummy =1 if right	0.2699594* (0.1585419)	No
Having the information about the interest included if a sale is made in instalments is a basic consumer right. (True or false)	dummy =1 if right	0.7296669**** (0.2271173)	No
In Brazil, in 2013 what was the level of inflation? (3 alternatives or not know)	dummy =1 if right	0.4625293**** (0.0978709)	No
How would you rate your level of financial knowledge on a scale of 1 to 5 where 1 is not at all knowledgeable and 5 is very knowledgeable? (1 through 5, not know or refusal)	1 through 5	0.2480314**** (0.0506277)	Yes
Suppose you borrow R$100 from a friend and pay him back R$100 after a week. How much interest have you paid on this loan? (3 alternatives or not know)	dummy =1 if right	0.3791915*** (0.1286657)	Yes
An investment with a high return is likely to be high risk. (True or false)	dummy =1 if right	0.3570646*** (0.1301839)	Yes

significant at: **** 0.1%, ***1%, **5%, *10%

Endogeneity aside, from Table 5.1.1 we can infer, for example, that the ability to divide is 3.6 times more effective in increasing the factor than knowing that is a good idea to have a budget.

We use the minimum and maximum theoretical values of the knowledge and standardize it to vary between 0 and 100, we obtain the distribution in Graph 5.1.1, corresponding to a mean of 71.58203 and a standard deviation of 16.40562.

Graph 5.1.1

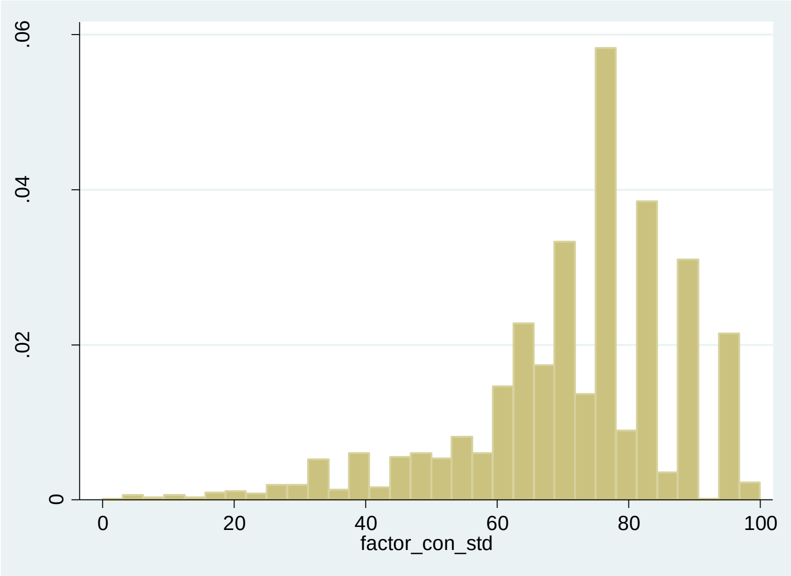


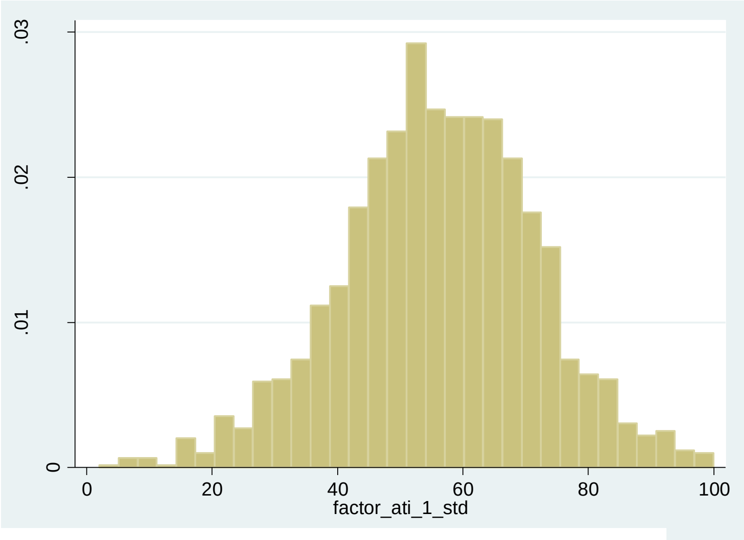
Table 5.1.2 contains the questions used to compute attitude factor 1 and their coefficients. Interestingly, these questions are concentrated in the topic of expenditure control and the perception of financial welfare and indebtedness.

Table 5.1.2 – Questions entering the Financial Attitude Factor 1

Question	Value assigned	Coefficient (Std. Dev.)	OECD survey
How would you rate your level of financial stress? (1 through 5, not know or refusal)	1 through 5	0.2529825**** (0.0498475)	Yes
I keep a close personal watch on my financial affairs (How much do you agree, 1 through 5)	1 through 5	0.1129368*** (0.0437404)	Yes
I prefer to pay for a purchase in instalments than to wait until I have the money to pay for it upfront. (How much do you disagree, 1 through 5)	1 through 5	0.0636214** (0.0315477)	No
I find it more satisfying to spend money than to save it for the long term (How much do you disagree, 1 through 5)	1 through 5	0.1067229**** (0.0333349)	Yes
I have too much debt right now (How much do you disagree, 1 through 5)	1 through 5	0.1110599*** (0.0350242)	Yes
I am satisfied with my present financial situation (How much do you agree, 1 through 5)	1 through 5	0.1346513**** (0.0353915)	Yes

significant at: **** 0.1%, ***1%, **5%, *10%

Graph 5.1.2



← impulsiveness control→

Following the same standardization procedure used for the knowledge factor, we obtain the distribution in graph 5.1.2 for Attitude 1 coefficient. It presents a mean of 56.17893 and a standard deviation of 15.53539. Table 5.1.3 contains the questions that the procedure selected for attitude factor 2. In this case we notice the main common topic is planning.

Table 5.1.3 – Questions entering the Financial Attitude Factor 2

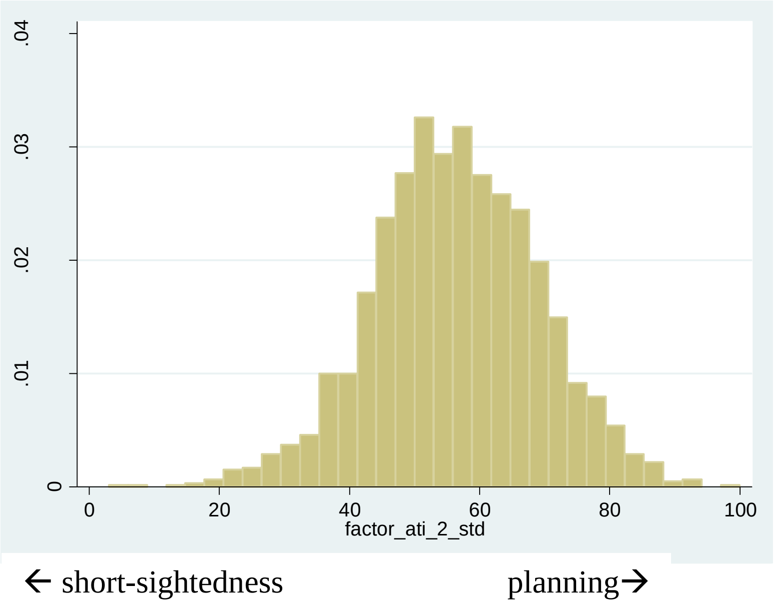
Question	Value assigned	Coefficient (Std. Dev.)	OECD survey
In general, I feel capable of managing my personal finances by myself (How much do you agree, 1 through 5)	1 through 5	0.1002954*** (0.0345982)	No
How confident are you that you have done a good job of making financial plans for your retirement? (How much do you agree, 1 through 5)	1 through 5	0.0875806*** (0.0314241)	Yes
I set long term financial goals and strive to achieve them (How much do you agree, 1 through 5)	1 through 5	0.0573925** (0.026377)	Yes
Q1B_14 Money is there to be spent (How much do you disagree, 1 through 5)	1 through 5	0.0738186*** (0.0285882)	Yes
I pay my bills on time (How much do you agree, 1 through 5)	1 through 5	0.0988449*** (0.0351348)	Yes
My financial situation limits my ability to do the things that are important to me (How much do you disagree, 1 through 5)	1 through 5	0.0672984** (0.0271841)	Yes
I must admit that I purchase things because I know they will impress others (slightly different phrasing[13]) (How much do you disagree, 1 through 5)	1 through 5	0.0662278** (0.0265752)	Yes

significant at: **** 0.1%, *** 1%, ** 5%, * 10%

Graph 5.1.3 displays the distribution for the standardized Attitude 2 factor, which has a mean of 56.29458 and a standard deviation of 12.72397.

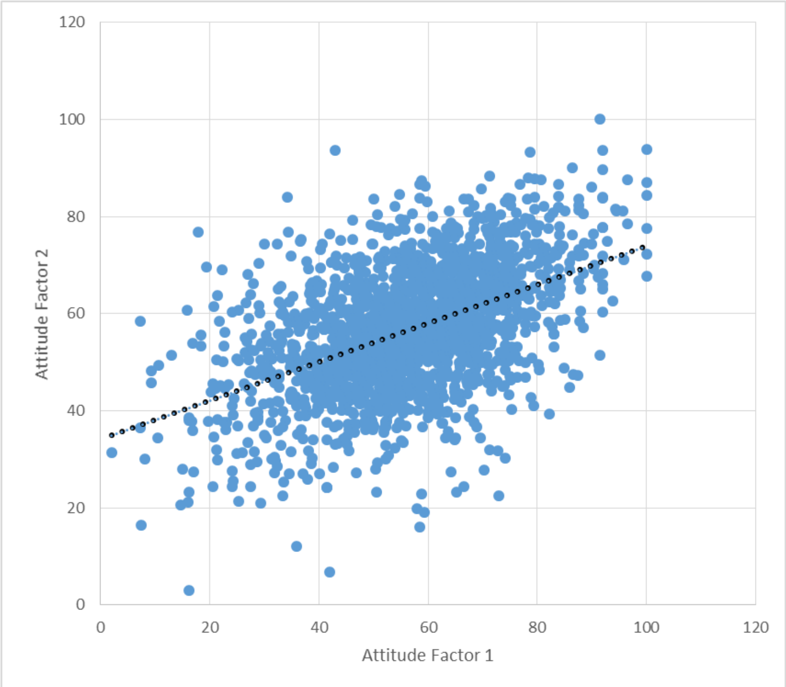
[13] Literal translation is "When I buy something, I generally choose a brand my friends/relatives will approve of".

Graph 5.1.3



Correlation between factors is low. It is 0.09 and 0.20 between the knowledge factor and, respectively, attitude factors 1 and 2. We would expect the correlation to be high between both the attitude factors, since we relate control with the ability to plan, but it is only 0.49. The observed joint distribution is plotted in Graph 5.1.4.

Graph 5.1.4 -Joint distribution of attitude factors



We follow van Rooij et al (2011) and show how the factors we identified vary across demographics in tables 5.1.4 through 5.1.6.

Table 5.1.4 - Knowledge Factor across demographics

	Knowledge Factor quartiles					
Education	1(low)	2	3	4 (high)	Mean	N
Illiterate	62.86	18.57	7.14	11.43	53.39701	70
Literate with no formal education	45.45	18.18	9.09	27.27	63.01518	11
Some primary level school	40.82	25.13	19.79	14.26	66.36166	561
Complete primary level school	30.23	19.07	28.37	22.33	71.06362	215
Some secondary level school	24.69	25.93	26.54	22.84	71.72241	162
Complete secondary level school	20.74	23.1	24.79	31.37	74.18523	593
Some university level education	14.04	21.91	24.16	39.89	77.74717	178
Complete university level	8.89	14.44	22.22	54.44	81.26779	180

Pearson chi2(27) = 253.9777 Pr = 0.000

	Knowledge Factor quartiles					
Age	1(low)	2	3	4 (high)	Mean	N
16-19 years	28.47	22.63	20.44	28.47	71.68813	137
20-29 years	25.86	24.03	23.34	26.77	72.50594	437
30-39 years	23.96	20.88	23.52	31.65	72.92571	455
40-49 years	25.75	23.85	23.85	26.56	72.64131	369
50-59 years	30.8	19.38	21.45	28.37	70.89494	289
60-69 years	33.18	23.04	23.96	19.82	68.28699	217
70 years and older	45.45	24.24	18.18	12.12	63.90118	66

Pearson chi2(18) = 32.0591 Pr = 0.022

	Knowledge Factor quartiles					
Gender	1(low)	2	3	4 (high)	Mean	N
Female	31.88	23.84	21.32	22.97	69.6275	1032
Male	23.24	20.79	24.63	31.34	73.73244	938

Pearson chi2(3) = 30.3935 Pr = 0.000

Table 5.1.5 - Attitude Factor 1 across demographics

	Attitude Factor 1 quartiles					
Education	1(low)	2	3	4 (high)	Mean	N
Illiterate	8.96	17.91	25.37	47.76	64.19915	67
Literate with no formal education	10	40	30	20	58.28978	10
Some primary level school	24.82	24.46	26.63	24.09	56.10494	552
Complete primary level school	28.91	27.01	24.64	19.43	54.45728	211
Some secondary level school	24.39	31.71	22.56	21.34	55.49169	164
Complete secondary level school	25.57	25.39	26.43	22.61	55.36477	575
Some university level education	29.94	24.29	20.34	25.42	55.08551	177
Complete university level	21.47	19.21	22.6	36.72	59.68195	177

Pearson chi2(27) = 55.1231 Pr = 0.001

	Attitude Factor 1 quartiles					
Age	1(low)	2	3	4 (high)	Mean	N
16-19 years	28.24	27.48	17.56	26.72	55.82609	131
20-29 years	25.93	25	26.39	22.69	55.37239	432
30-39 years	29.53	27.29	22.82	20.36	53.97741	447
40-49 years	27.47	23.63	26.1	22.8	54.73367	364
50-59 years	23.93	22.5	27.5	26.07	56.97328	280
60-69 years	15.35	24.65	26.05	33.95	61.0329	215
70 years and older	3.13	23.44	26.56	46.88	66.1599	64

Pearson chi2(18) = 58.0052 Pr = 0.000

Table 5.1.5 - Attitude Factor 1 across demographics (cont.)

Gender	Attitude Factor 1 quartiles 1(low)	2	3	4 (high)	Mean	N
Female	29.24	24.38	22.6	23.79	54.82469	1009
Male	20.35	25.65	27.71	26.3	57.65775	924

Pearson chi2(3) = 21.8146 Pr = 0.000

Table 5.1.6 - Attitude Factor 2 across demographics

Education	Attitude Factor 2 quartiles 1(low)	2	3	4 (high)	Mean	N
Illiterate	20.78	25.97	31.17	22.08	56.76947	77
Literate with no formal education	16.67	50	0	33.33	57.27187	12
Some primary level school	26.04	27.60	24.31	22.05	55.35406	576
Complete primary level school	32.57	21.56	22.48	23.39	54.31464	218
Some secondary level school	29.52	29.52	24.7	16.27	53.51446	166
Complete secondary level school	22.77	27.66	26.98	22.6	56.33316	593
Some university level education	26.67	18.33	25.56	29.44	56.84166	180
Complete university level	16.11	10.56	24.44	48.89	63.32364	180

Pearson chi2(27) = 112.9513 Pr = 0.000

Age	Attitude Factor 2 quartiles 1(low)	2	3	4 (high)	Mean	N
16-19 years	34.53	28.78	23.02	13.67	52.07305	139
20-29 years	26.53	26.98	23.81	22.68	55.45235	441
30-39 years	27.41	25.44	27.41	19.74	54.94916	456
40-49 years	25.67	22.46	22.99	28.88	56.76752	374
50-59 years	20	24.07	24.75	31.19	58.39707	295
60-69 years	18.3	22.32	30.36	29.02	58.87992	224
70 years and older	19.18	23.29	20.55	36.99	58.97271	73

Pearson chi2(18) = 48.6349 Pr = 0.000

Gender	Attitude Factor 2 quartiles 1(low)	2	3	4 (high)	Mean	N
Female	27.67	25.29	24.05	23	55.39581	1048
Male	22.01	24.32	26.42	27.25	57.28193	954

Pearson chi2(3) = 11.3231 Pr = 0.010

Some general features are worth pointing out. First, the knowledge factor increases monotonically with the level formal education, whether both attitude factors follow a U-shaped curve, reaching the lowest averages around complete primary - some secondary schooling. When age in concerned, although this cannot be separated from a cohort effect, the knowledge factor follows and inverse U-shaped curve, peaking at people in their thirties, the same group that displays the lowest average value of attitude factor 1. Attitude factor 2 seems to generally increase with age. Finally, gender indicates higher average values for men. Regarding financial knowledge, the general patterns of these variations along formal education, age and gender are common findings in the literature, as reported by Lusardi & Mitchell (2014), including van Rooij et al. (2011).

5.2. Factor coefficients

Table 7.2.1 – Factor Coefficients in Behavior Equations

Dependent Variable	Knowledge Factor	Attitude Factor 1 (Control)	Attitude Factor 2 (Planning)
Saving last 12 months	1 (fixed)	1 (fixed)	1 (fixed)
Saving last 12 months (instruments)	0.810809**** (0.0974260)	0.5789455**** (0.1027399)	0.9293637**** (0.2131022)
Making household budget	0.4281325**** (0.0923696)		1.3091600**** (0.3887332)
Prepared for unexpected negative income shocks	0.5211094**** (0.1249246)	1.3130260**** (0.2191498)	0.8395531*** (0.3274245)
Retirement planning	0.1898849** (0.0887439)		1.6243480**** (0.4734712)
Having a credit Card	0.6478369**** (0.1289552)		
Using checking account overdraft	0.7450375*** (0.2705077)	-0.9196547*** (0.2930178)	
Using payroll consigned credit (wage collateralized)	2.207925**** (0.6258796)	-2.738474**** (0.6613689)	4.4134010*** (1.5049140)
Use of general purpose financial system loans	0.7825438*** (0.2810842)	-1.6565480**** (0.3757118)	1.3940450** (0.6436855)
Using merchant credit (carnê de loja)	0.2668460*** (0.0963622)	-0.2741989** (0.1275451)	
Vehicle financing	0.7496158** (0.3106971)	-0.9374941*** (0.3226879)	1.3069650** (0.6113097)
Having a savings account	0.9408200**** (0.1690471)	0.3341289** (0.1349187)	

significant at: **** 0.1%, ***1%, **5%, *10%

In this section, we present the coefficients obtained for each factor in each financial behavior equation. They correspond to the γ_i in equation system (3).

The knowledge factor is significant and positive in all the equations. Broadly speaking, in Brazil a payroll consigned credit costs about half of using personal loans and this cost less than a third than using checking accounts overdrafts. The coefficients preserve this ordering, meaning that a knowledge factor increase should incentive more the use of cheaper credit.

As we have mentioned, the desirability of using credit is not clear-cut. While it is easy to argue that generally having access to credit increases welfare, we cannot say the same about its usage, especially in environments with high interest rates, given the possibility of losing control of consumption. Interestingly, it seems that this ambiguity is captured by the attitude factors. Both attitude factors relate to saving and preparedness variables, while credit usage variables are negatively affected by attitude factor 1 (control) and positively affected by factor 2 (planning). Additionally, Factor 2 in not significant for either checking account overdraft use (the most expensive credit line included) or for retailer credit, which is most frequently used for consumption.

Another remarkable feature is that financial knowledge and attitude are significant, while controlling for one another. This rejects the hypothesis that knowledge affected behavior only by having an effect on attitudes.

5.3. Other relevant knowledge and attitude questions

Although the variables of knowledge and attitude that were not presented in the previous subsections did not enter the knowledge or attitude factors, we allow them to affect behavior attitudes separately, thus keeping them as extra controls where significant. These results are available upon request.

6. Endogeneity and Instrumentation

The literature on financial literacy and inclusion has drawn attention to the fact that attitudes and knowledge variables are probably endogenous to behavioral outcomes. First, both the regressors and the outcomes may be affected simultaneously from other variables. This would generate omitted variables bias and the standard way to deal with it is by including controls, especially demographics, to proxy individuals characteristics (see, for example, Lusardi & Mitchell(2007a), van Rooij et al(2011)).

Secondly, there may be reverse causality since outcomes regarding financial behavior may affect knowledge and attitude. For example, this happens if having a savings account helps individuals to learn how to perform compound interest calculations. Bachmann & Hens (2015) show concern that it might be that, instead of more informed individuals being more prone to seeking expert advice for investments, it could be that individuals who use their services become more informed.

Both sources of endogeneity may be addressed by finding a proper set of instruments, which is a complex task. Some very smart instruments have been found by the literature. For example, Lusardi and Mitchell (2011) use the mandated financial literacy high-school education as an instrument for financial literacy to measure its impact on retirement planning, while Alessie, Van Rooij & Lusardi (2011) use as instrument the individual´s assessment of parents and sibling financial knowledge.

In spite of the diversified set of instrument variables employed in different studies, the pattern of finding an impact (much) larger[14] of financial knowledge when using instruments is recurrent in the literature, as seems to be the

[14] For instance, Lusardi and Mitchell (2011) find a coefficient more than 5 times larger when using their instrument.

general performance of first stage regressions, which is generally not outstanding[15]. Our results are in line with these aspects, although we do not have natural experiments or questions designed to work as instruments in the survey.

We use the system of equations structure to find exogenous variables that can become “instruments”. All variables seem *ex-ante* to belong in the equations. However, many profile variables (gender, formal education, age, income, activity, size of the municipality, etc.) are not significant in some equations. This means that a combinations of these observables, is not perfectly collinear with controls. Intuitively, this is like saying that we can use as instrument an exogenous variable that was not significant as control in the endogenous version of the equation. Although we cannot expect much from this approach, since correlation between these variables and those we want to instrument (namely the knowledge and attitude) is not foreseeably high, it seems that the performance of this approach depends on the particular application.

For the present application, a first stage regression of the knowledge factor on “instruments” (after excluding those with p-value higher than 0.10) attained and R^2 of 0.16 (and an F statistic of 28.96[16]). For the other factors, this was below 0.10.

Thus, we try to explore the instrumentation of the knowledge factor to add some knowledge about the endogeneity of our previous results. We proceed in the following steps:

1 – Estimate the endogenous regression presented before;

2 – Obtain the predicted values for the knowledge factor;

3 – Bootstrap steps 3.1 through 3.3[17]:

> 3.1 – Regress the predicted knowledge factor against selected controls;
>
> 3.2 – Predict knowledge factor in sample
>
> 3.3 – Run a nonlinear SUR substituting the predicted knowledge factor for the combination of variables used to obtain the knowledge factor in step 1.

The results are presented in table 6.1, paired with the previous results for comparison. Most of the coefficients that multiply the knowledge factors become not significant. It is hard to tell whether this results from former endogeneity or from the weakness of the instruments.

However, 5 coefficients are found significant, and all of them seem to indicate a downward bias in the regression without instruments, following the pattern of many studies, as we have pointed out. Although the literature has

[15] This happens in Fornero and Monticone (2011), Klapper, Leora F., Georgios A. Panos. (2011), and in Sekita (2011) and Agnew, J., Bateman, H., & Thorp, S. (2013).

[16] This compares with the first stage results in Alessie, van Rooij & Lusardi(2011)a, see their table 6. They use two specific questions to instrument financial knowledge: how the surveyed individual compares his oldest sibling´s financial knowledge to his own and how he rates his parents’ knowledge. In first stage regressions with different definitions of the dependent variable, the authors obtain R^2 of 0.170 and 0.237 and F-statistics of 9.608 and 19.37, similar to Agnew, Bateman & Thorp, S. (2013). Fornero and Monticone (2011) use other instruments, with similar performance.

[17] 500 replications. 464 after failures.

emphasized omitted variables and measurement error as the main possible sources of this bias[18], this is what we would expect if there were a positive feedback effect from learning by participating in mind. Suppose increases in financial knowledge increase the chance that individuals present behaviors related to financial inclusion, but that, once these behaviors take place, people learn more about the theme. Thus, our dataset would pair the financial behavior with inflated knowledge, as compared with the knowledge level that "caused" the behavior. Thus the larger the feedback, the larger (in absolute value) the downward bias in the regression without instruments.

Our estimations indicate the largest downward bias in the credit-card equation, which is reasonable since this product has presented very high expansion in the last few years, representing the first contact with a financial product for many people. Considering the period between the first quarter of 2008 and the last quarter of 2014, the expansion of issued general-purpose credit cards was 34% (25% if we consider only cards with at least one transaction in the preceding year) [19]. Remember, as pointed out in section 4, that this is the most widely used instrument in the sample (45%). In Brazil, the process for obtaining a credit card does not involve a long period to obtain a credit score, as opposed to the US. On contrary, in many situations it is simpler to obtain a credit card than a bank account. Issuer banks have the incentive to offer credit cards, since the make the interchange fee revenue on purchases and they do not incur in the cost of the money in time, since on average, they receive bill payments before they pay merchants. This is very different from the setting in other countries and has historical reasons related to high inflation periods in the late 20th century. In addition, high interest rates[20] in revolving credit and several service charges provide extra incentives to issuer banks and make an environment where customers need to learn fast[21]. The estimations also indicate a relevant feedback to knowledge from making a budget. Still, some coefficients are very close, namely those in the equations explaining "Saving last 12 months (instruments)" and "Having a savings account".

[18] See, for example, Behrman et al.(2012)
[19] Data from the Brazilian Central Bank, available at http://www.bcb.gov.br/?SPBADENDOS .
[20] For example, in the period of 10 to 16 February 2016 the annual percent rates posted by the Central Bank ranged between 60.59% and 887.04%, depending on the creditor. The Central Bank publishes this information to aid individuals in financial institution choice.
[21] See Agarwal et al. (2008) for an analysis of these incentives in the US.

Table 6.1 – Knowledge Factor Coefficients: Original X Instrumented

Dependent Variable	Knowledge Factor Original	Knowledge Factor instrumented
Saving last 12 months	1 (fixed)	1 (fixed)
Saving last 12 months (instruments)	0.810809**** (0.0974260)	0.8604073**** (0.2217725)
Making household budget	0.4281325**** (0.0923696)	0.7621918*** (0.283045)
Prepared for unexpected negative income shocks	0.5211094**** (0.1249246)	0.8257046** (0.3586319)
Retirement planning	0.1898849** (0.0887439)	-.0241579 (0.3079852)
Having a credit Card	0.6478369**** (0.1289552)	3.64547*** (1.175741)
Using checking account overdraft	0.7450375*** (0.2705077)	2.176868 (12.69759)
Using payroll consigned credit (wage collateralized)	2.207925**** (0.6258796)	1.439248 (79.09333)
Use of general purpose financial system loans	0.7825438*** (0.2810842)	0.9357506 (1.983203)
Using merchant credit (carnê de loja)	0.2668460*** (0.0963622)	0.3241551 (0.234084)
Vehicle financing	0.7496158** (0.3106971)	5.157396 (93.91503)
Having a savings account	0.9408200**** (0.1690471)	1.090267**** (0.2336668)

significant at: **** 0.1%, ***1%, **5%, *10%

7. Conclusion

In the present paper, we build a new regression based technique that serves two purposes. The first one is to combine variables and generate measures of knowledge and attitude designed to be good predictors of policy objective (behavior) variables, in the presence of controls. In the case of financial behaviors, this is interesting because it ensures we are analyzing questions that really matter. When we compare our results with the commonly used factor analysis for attitude variables, we find that the new technique selects variables from different traditional factors, without requiring them to be correlated among themselves and, at the same time, provides a natural way to obtain weights and to avoid skewing measures with several questions that convey similar information. On the other hand, factors keep the distributions features along observables found in the literature.

The other purpose is to provide coefficients that, endogeneity aside, may be used to compare in a simple and direct way among different policy instruments that influence different policy objectives. In our econometric application, we find that several variables that indicate behaviors related to financial inclusion are affected in a "proportional" way by variables of financial knowledge that could be targeted by financial education programs. This means that teaching people a certain content may serve many purposes and it is not necessary to choose among them.

At the same time, the technique can be used to provide some guidance about contents that are not correlated with policy objective, which are less interesting to have resources spent on, although we should be cautious about endogeneity. The treatment for endogeneity that we provide indicates the expected downward bias in non-instrumented estimations, which can be explained by the learning by using financial products or by presenting other financial behaviors.

Finally, taking advantage of the system structure to find instruments allows us to obtain instrumented results that are in line with those in the literature for financial knowledge, both in first stage regressions performance and in the fact that instrumented coefficients are larger. The latter result is expected, because of the feedback of inclusion behavior to financial knowledge.

As a future research agenda, it would be interesting to apply the technique to other datasets, where we can find some genuine instruments to obtain improved results combining both approaches.

Furthermore, we believe the technique we propose is flexible enough to be applied to several other settings, by adequately choosing the function relating the factors and controls to the outcomes. Thus, event count could be represented as Poisson and a Gamma distribution could be used for strongly asymmetric outcomes. Interesting applications would be relating economic outlook variables and profile variables to delinquency; relating organizations structures (like governance, management type, supplier structure, human resources policy, etc.) to firm performance (profitability, market value, growth, market share, etc.); or combining expectation variables into factors that predict macroeconomic outcomes, like inflation, unemployment and investment.

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