Personalized Information as a Tool to Improve Pension Savings: Results from a Randomized Control Trial in Chile*

Olga Fuentes† Jeanne Lafortune‡ Julio Riutort§ José Tessada¶
Félix Villatoro‖

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Abstract

We randomly offered to workers in Chile personalized versus generalized information about their pension savings and forecasted pension income. Personalized information increased the probability and amount of voluntary contributions after one year without crowding-out other savings. Moreover, this change was strongest for those who also overestimated their pension income at the time of the intervention. Thus, a person's inability to understand how the pension system affects them may partially explain low pension savings. Despite the significant response to the intervention, its temporary nature and size suggest that information should be combined with other elements to increase its efficiency.

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†Superintendencia de Pensiones. Email: ofuentes@spensiones.cl.

‡Pontificia Universidad Católica de Chile and JPAL. Email: jlafortune@uc.cl.

§Universidad Adolfo Ibáñez. Email: julio.riutort@uai.cl.

¶Pontificia Universidad Católica de Chile and FinanceUC. Email: jtessada@gmail.com.

‖Universidad Adolfo Ibáñez. Email: felix.villatoro@uai.cl.

1 Introduction

Many countries are facing aging populations, which might lower their ability to provide acceptable living standards to the elderly. Most of these countries, furthermore, have opted to establish Defined Contribution (DC) pension systems instead of Defined Benefits (DB) ones, given their budgetary restrictions. While individuals participating in a DB system usually need only know their last x years of wage earnings to estimate their pensions, DC systems require a deeper understanding of complex financial concepts by the population (e.g. compound interest, expected returns, market fluctuations and the timing of investments), since actions taken while being active in the labor market directly translate into pension replacement rates upon retirement.[1] In this paper, we use a randomized control trial to see whether and how providing personalized information to individuals in a DC system alter their savings and labor supply decisions.

Our goal is to measure whether individuals who participate in the Chilean DC system, established over 30 years ago, are lacking the capacity to process generic information that is often provided to them and would be benefited by receiving personalized information. To focus on evaluating only the personalization of the information, we mention to all participants that there are three main ways to increase one's pension (increasing mandatory savings, increasing voluntary savings and delaying retirement). The difference is that, for the control group, we include how much each of these actions is likely to impact "on average" one's pension while for the treatment group, we include a personalized estimate of how each three actions will impact their estimated pension receipt compared to an estimate obtained when no change would be made to actual behavior. To alleviate the concern that the difference between the two treatments could stem from something else than personalization of the information, we elicited, before the intervention, the pension that each participant thought they would be receiving upon retirement. We then contrast the impact that personalized information had depending on whether the estimated pension we provided under the status quo was above, below or similar to the participants' belief. If personalized information affects behavior through channels other than updating an individuals' belief, we should anticipate a uniform impact of the treatment. However, if what is key is that individuals are reacting to the numbers they are being provided and thus readjust their prior, we should see a large difference depending on the type of "shock" we provided to participants.

The intervention consisted of a field experiment (randomized control trial) where eight self-service modules, all equipped with a pension simulation software (see Berstein, Fuentes and Villatoro, 2013, for a description of the software and assumptions used in the simulator), were installed in locations with a high flow of low-income individuals, namely governmental offices where social payments and services targeted to their needs are delivered. In Chile, those services have

[1] An example of the potential difficulties associated to grasping these financial concepts if given by Stango and Zinman (2009), who show that individuals tend to linearize exponential functions, which leads them to underappreciate the cumulative interest costs of long-term debt and the long-term gains from savings due to interest compounding.

been agglomerated into government offices called "Chile Atiende", of which there are 153 locations across the country, receiving on average 37,000 visits per year. We chose eight offices with a large volume of visits to install the self-service modules. The intervention considers a single treatment (receiving personalized versus generic information) and the allocation into treatment and control groups was made according to the last digit of their national ID number, splitting the sample into two equally sized groups.[2]

The treated individuals received a personalized estimate of their expected pension under different scenarios: status quo, increasing average number of months per year with a mandatory contribution to the system, increasing voluntary savings, and delaying retirement by one year.[3] Such estimates are calculated using administrative data that is matched to the regulatory authority database, the Superintendencia de Pensiones (SdP), using the national ID number. At the time of the simulation, the individual is faced with his/her actual situation in terms of the level in his/her saving account, density of contributions, income level, fund type, etc.[4] In order to make sure that our intervention does not simply increase the salience of pension savings or produces a "nudge" to individuals to talk about their pension savings, the control group is also reminded that savings for retirement are important. The control group received *general* information and the same recommendations on how to improve their future pensions but without any reference to their individual situation. We contrast the response of individuals according to the difference between the expected and the baseline pension estimate in order to control for differences between the personalized and generic information in terms of format, visual presentations, numeric representation, etc.[5] We argue that these other differences should affect participants in a way that is orthogonal to their anticipated pension receipt while the personalization of information would not. We also explore whether the personalization of the actions versus that of the expected pension appears to be more relevant.

Our intervention should be irrelevant in a neo-classical framework without information fric-

[2]While national ID numbers are given by birth or immigration date and thus are not random, the last digit, preceding the "verification" character is not correlated with age, gender or any relevant characteristic of the individual. The ID numbers consist of a six to eight digit number followed by the verification character, determined by the previous numbers, in a "xx.xxx.xxx-y" format. We use the last digit before the hyphen for the randomization, that is the last x before the hyphen in the example before.

[3]Users could then request simulations with different parameters if they wished to do so but few actually did so.

[4]We only simulated the self-funded pension. For some (very) low-income individuals, the pension system also includes a subsidy that was not included in the calculations and that is computed when the person effectively retires. We don't include this type of subsidy in our simulations, since individuals must also fulfill residency and mean-tested requirements in order to become receipents of these benefits. Our data does not allow us to verify if these conditions are met by participants in our study or if they will be met at time of retirement.

[5]Goldstein, Hershfield and Benartzi (2016) conduct an experiment to explore how individuals' perception of the adequacy of savings varies according to whether their state balances are presented as lump sums or as annuities. The authors report that, for low income levels, annuities are perceived as less satisfactory than their lump sum equivalents, while the opposite holds for higher income levels. Also, middle-age participants considered a relatively small lump sum as more adequate than its annuity counterpart and they were less likely to increase savings rates when they were showed a relatively small lump sum instead of the equivalent annuity. The authors argue that the presence of this "illusion-of-wealth" effect may help to explain why individuals seem to under-annuitize upon retirement.

tions. Theoretically, the decision-making problem faced by a participant of a DC system is very similar to a life-cycle problem. The standard framework to analyze this problem (see, for instance, Modigliani and Brumberg 1954, Modigliani and Brumberg 1980, Merton 1969, and Samuelson 1969) assumes that individuals are rational decision makers, concerned about maximizing their life-long expected utility and that they have access to and are able to understand a great deal of relevant information (e.g. future wages, interest rates, longevity, returns, and so on). Moreover, these individuals determine their optimal consumption, savings and investment strategies, and are able to commit to their savings plans. In this type of setup, optimal consumption and savings decisions are affected by factors such as: subjective discount factors, risk aversion, investment horizon and amount of wealth, among others. Our intervention does not affect these in any way.

Alternative models suggest that decisions may not be taken optimally because either individuals have preferences that are non-neoclassical or because they do not have the information required to take these decisions or they are unable to understand it because it is too complex. Thaler and Benartzi (2004) argues that individuals may lack self-control as well as having a tendency to procrastinate. Laibson (1997, 1996) note that in the presence of hyperbolic discounting, individuals may overestimate their capacity to save tomorrow, which has been argued to be consistent with empirical evidence as shown by Brown, Chua and Camerer (2009). Along these lines, Barr and Diamond (2008) argue that individuals tend to seek short-term gratification, which translates, for instance in opting for early retirement even though this reduces the amount of pensions. Another important factor that influences affiliates' decisions is the existence of inertia and myopic behavior (See for example Agnew, Balduzzi and Sunden, 2003; Madrian and Shea, 2001; Mitchell, Mottola, Utkus and Yamaguchi, 2006). Even with neoclassical preferences, determining an adequate savings rate can be a complex task. Benartzi and Thaler (2007) point that, individuals usually do not spend much time calculating a personal optimal savings rate, adopting mostly simple rules of thumb, which may lead to systematic biases. Thus, by providing information that is easier to understand because it is personalized to the individual's situation instead of describing the condition of a generic individual, we may alter decisions of participants.

By focusing on personalized information linking actions with quantifiable outcomes, we hypothesize we can help people recognize the link between their contributions today and the level of pension they will obtain at the moment of retirement and through that, modify their savings behavior. We think this hypothesis is a valid one in our context since Chileans show little financial knowledge, and in particular scarce knowledge and understanding of the pension system (see Berstein, Fuentes and Torrealba, 2010). Participants in our sample are more knowledgeable than Chilean averages but still have very limited information and understanding of the pension system. Low levels of financial literacy may be detrimental for individuals (see for example Hastings, Mitchell and Chyn, 2010; Mitchell, Todd and Bravo, 2007). Furthermore, lack of financial knowledge is not unique to Chile. Indeed, Lusardi and Mitchell (2005) and Lusardi and Mitchell (2008) find evidence of low levels of financial knowledge for the U.S., especially among women, low-income individuals, minorities and immigrants and argue that this may be detrimental to pension savings (Behrman, Mitchell, Soo and Brava, 2012).[6] Thus, our results may be applicable to other regions where similar low financial literacy exists.

To test these hypotheses, this project uses data from three different sources: administrative data obtained from the SdP, a baseline survey conducted before the intervention, and a follow-up survey designed to understand the process leading to possible behavior changes. The administrative data contains information about demographic characteristics, mandatory and voluntary savings, labor status (as reflected in monthly contributions) and variables related to the fund management of individuals affiliated to the system. On the other hand, the baseline survey covers topics associated with labor status and income to complement administrative data (specially for non affiliates), while it also gathers information about expected pensions and financial knowledge. Finally, the follow-up survey is conducted about one year after exposure to the self-service modules and covers topics related to their understanding of the pension system, savings outside the pension system, confidence in the system, and characteristics of the self-attention module. The intervention took place between August 2014 and February 2015 and 2,546 individuals participated, 95% of which were affiliated to the system. Since we see no change in affiliation correlated with the treatment, we argue that attrition in the administrative data will be of little concern. Administrative data is available up to 12 months after treatment and the follow-up survey was conducted between October and December 2015.

Using the administrative data, we find evidence that voluntary savings significantly increased on average for those who received personalized compared to generic information. The estimated impact represents an increase of about 12 percent in terms of the voluntary savings made by participants. This is driven partly by an increase of about 1.5 percentage points in the number of individuals making a voluntary contribution. While small, this corresponds to an increase of around 30 percent in the fraction of individuals making at least one contribution of this type. We find no response in other types of pension fund actions which is comforting since our intervention did not offer any information regarding pension fund administration. We also observe an increase in the probability of retiring among those in the treatment group. All these results are concentrated in the first 6 months after the intervention, fading in the second semester after the intervention. This implies that while relevant, these added savings are too limited to impact long-term pensions without complementary interventions. Finally, in our phone survey, we find that personalized information made the intervention more salient and better evaluated by the participants. We also find that it raised their self-reported knowledge and valuation of the pension system.

[6] However, Hastings, Madrian and Skimmyhorn (2013) argue that, even though there is ample evidence of the positive correlation between financial literacy and retirement planning, savings and wealth accumulation, more research is needed regarding causality of that relationship. See Lusardi, Michaud and Mitchell (2017) for a model of endogenous financial literacy.

Key to our argument, we find that our increase in voluntary savings is concentrated amongst individuals who had previously overestimated their expected pension. Complementing this, we also see that individuals who received personalized information and had overestimated their expected pension saved more outside the system, suggesting limited crowd-out. On the other hand, for individuals who had underestimated how much the system would provide them, we see a decrease in mandatory contributions (implying lower labor supply or lower formal employment) and a decrease in savings intentions. These results emphasize the role of information, versus "nudging" as the likely channel of action in our context. However, we also see an increase in retiring for those individuals who received "bad news" suggesting that personalized information may also lead to discouragement for some individuals close to retirement age. We find more limited role for providing a personalized impact of different actions, suggesting that offering a value for the projected pension was more key than personalizing the impact of given actions. Those who respond the most to "bad" and "good" news are those with the lowest knowledge of the pension system and with lowest educational attainment, suggesting that this information may be particularly relevant for poorer and less knowledgeable individuals.

Chile is an interesting setting to study this question since it was one of the first developing countries to implement a defined contribution pension system in 1981. The system requires all formal employees (and self-employed workers since 2014) to contribute 10 percent of their monthly taxable income to a pension fund administrator of their choice. The first generation of individuals who started working in the labor force under the new system is now nearing retirement age and there is a lot of public criticism made about the level of pension they will be able to obtain for their retirement. It is thus key to understand whether more information can help improve pensions or if more active interventions will be required.

Information provision has been shown to play a role in increasing participation into new pension plans (Duflo and Saez, 2002), delaying retirement age (Mastrobuoni, 2011; Miranda Pinto, 2013) and effectively responding to incentives to increase pension savings (Duflo, Gale, Liebman, Orszag and Saez, 2005; Mastrobuoni, 2011). Additionally, to be exposed to an educational event impacts members' savings expectations and their specific retirement goals (Clark, d'Ambrosio, McDermed and Sawant, 2006), influencing them to take decisions to improve their future pension. Our innovation lies in comparing the personalization of information instead of information per se.

Two existing studies used non-experimental methods to measure the impact of providing pension projections: Fajnzylber and Reyes (2015) in Chile using matching techniques and Dolls, Doerrenberg, Peichl and Stichnoth (2018) in Germany using an event study. In addition to the use of experimental variation, our main contribution is to be able to contrast personalized versus generic information instead of versus a control that receives nothing. This allows us to exclude the role of simply making pensions more salient to the mind of the recipient. Additionally, our "one-on-one" delivery of the information improves the precision of our estimates compared to mail delivery in the case of these two studies. Moreover, our field experiment design allows us to capture heterogeneity by expectations regarding future pension which turns out to be relevant since the effect of the information we provide differs precisely in that dimension.[7]

The closest paper to our research is Goda, Manchester and Sojourner (2014), which studies the impact of providing retirement projections on individuals's contributions to retirement accounts in the context of a single firm and for complementary accounts in a country with a defined benefit system. In spite of the similarities our contribution differs from theirs in many ways. First, for most outcomes, they cannot statistically distinguish between the impact of providing personalized information with receiving generic information, which is the focus of our paper. Second, our setting implies that we can measure the impact of information on (almost) the entire formal pension savings *and* that we can provide more concrete information about "retirement" income and not just about "retirement savings", something impossible to do only with employer-related plan data in the context of the United States' Social Security system. Third, while Goda et al. (2014) focuses on voluntary savings, due to the nature of our database, we are able to provide more evidence regarding the labor market outcomes of our intervention, which include formal employment and retirement decisions. Goda et al. (2014) find that providing income projections increases contributions by about 3.6% on average compared to the group which received no information but providing workers with simple knowledge on how to change one's contribution has significant impact on contribution density as well. Our estimated marginal impacts of providing personalized vis-a-vis generic information are larger, a result that is not surprising if the information is more enlightening. In addition, our study is representative of a broader group, among the Chilean population, which includes low and middle income people, as well as lower education individuals and informal workers, self-employed and inactive system affiliates, and captures almost all of the pension contributions by these individuals. This is a group that is usually not targeted by employer-sponsored retirement plans in the US.

While we are one of the first papers randomly assigning personalized versus general information in the context of a pension system, many other works have looked at the role of information on savings. Goldberg (2014) reviews a set of existing studies and argues that there is very limited effect of financial-literacy interventions on savings rate. In particular, two studies for Indonesia, Cole, Sampson and Zia (2011) and Carpena, Cole, Shapiro and Zia (2011) both show no impact of interventions which increased financial literacy on savings. It may be that generic information is simply unlikely to change behavior.

We test whether the information we provided influenced labor supply decisions, in particular the formalization of employment. This is because the pension deduction may be seen as a pure

[7] Fajnzylber and Reyes (2015) did not have data on expectations while Dolls et al. (2018) only showed that most participants overestimated their pension.

tax by employees, thus reluctant to enter the formal labor force. However, once they are shown the benefits in terms of pension value these contributions may generate, they may be more likely to enter into formal contracts, despite these additional deductions. This has been emphasized previously, for example, Kumler, Verhoogen and Frías (2013) show that in Mexico, a pension reform that put more weight on past wages did increase the amount of wage payment officially declared by employers. In our context, we find limited role for this channel to be at play.

Finally, a recurring topic for academics and policy makers is whether individuals have adequate savings levels. This concern is valid even for DC pension systems, which seem to suffer from low contribution rates and low accumulation even when they are mandatory (see, for instance, Munnell, Webb and Delorme 2006 and Federal Reserve 2014 for the US case and OECD, World Bank, IDB 2014 for Latin America). This lack of appropriate savings, among other observations, has led to postulate that, in practice, individuals' behavior may be different from that predicted by the standard life-cycle hypothesis[8] However, answering the question "How much should individuals save?" is not an easy task. For instance, the World Bank recommends a replacement rate of 54%, defined in terms of final earnings (see Pordes 1994) and the International Labour Office establishes a minimum of 40% (see International Labour Organization 1952). From an academic perspective, Thaler and Benartzi (2004) suggests that a replacement rate (defined as the ratio of retirement income to pre-retirement income) between 70% to 100% would be acceptable. However, Skinner (2007) argues that whether optimal consumption should increase, decrease or stay constant at retirement depends on the assumptions about intertemporal elasticities of household production, consumption and leisure. Moreover, the same author provides references of empirical studies with contradicting results regarding the values of this key parameters. Overall, our results suggest that individuals appear to have a clear objective and respond to information in a way that is consistent with that objective. This would suggest that the view that individuals are "under-saving" should not be considered as a truth for all individuals since some of our sample appears to have previously been "over-saving".

The rest of the paper is organized as follows. The next section details the context of the pension system in Chile. Section 3 documents the experimental design, the empirical methodology and the data. The following section presents the results and the last one concludes.

2 Pensions Savings in Chile

To better understand the setting in which we undertook our experiment, this section describes the main elements of the Chilean pension system. Moreover, we also present the main elements of the pension simulator that the SdP currently offers on its web page. The information showed to

[8] On this topic, see the interesting account and discussion by Deaton et al. (2005).

participants in our experiment is based on a simplified version of the SdP simulator. The main features of this simplified simulator are also explained.

2.1 Legal and administrative background

In 1981, Chile was the first country in the world to privatize its pension system, moving from a traditional state-managed Pay-as-You-Go (PAYG) scheme to a privately managed defined contributions system with individual savings accounts. Reforms have been implemented over the years, including a major reform in 2008 (Law #20.255), which introduced a solidarity or basic pillar, providing protection for lower income groups. The SdP, as a public agency, is in charge of supervising and regulating Pension Fund Administrators, the public solidarity pillar and the old PAYG system that will eventually disappear.

Currently, the pension system is organized around a scheme of three basic pillars: (i) a poverty-prevention pillar, (ii) a contributory pillar of mandatory nature and (iii) a voluntary savings pillar. The combination of these components seeks to guarantee individuals the possibility of maintaining a standard of living similar across their active life and retirement stages and to eliminate the incidence of poverty among the elderly and disabled.

The first pillar, the solidarity pillar, is aimed at preventing poverty. This pillar consists of a non-contributory pension called the Basic Solidarity Pension (Pensión Básica Solidaria, or PBS), and a complement to the contributory pension called the Solidarity Pension Payment (Aporte Previsional Solidario, or APS). The PBS and APS are mean-tested benefits, targeted to the poorest 60% of the population.

The mandatory contribution pillar is a single nation-wide scheme of financial capitalization in individual accounts managed by single-purpose private companies called Pension Fund Administrators (AFPs for their name in Spanish). This is a defined contribution scheme, in other words, the contribution rate is determined and the benefits are calculated using actuarial formulas, according to the balance each individual has accumulated at retirement. Since its introduction, this pillar has required a monthly contribution rate of 10% of taxable income.[9] The coverage provided by the system, measured as the proportion of members to working-age population is around 79%. The individual accounts formed with mandatory contributions can only be managed by a Pension Fund Manager (hereafter, AFP, the acronym for their Spanish name, Administradora de Fondos de Pensiones).[10]

[9]For the purpose of pension (and health insurance contributions) the income is capped by the *tope imponible*. As of 2016, this cap is set at a monthly (annual) wage of approximately USD 2,792 (USD 33,500). Moreover, the cap is adjusted every year, according to the real annual growth in average wages.

[10]For each AFP, there is a fund choice among five funds, which are differentiated mainly by the proportion of their portfolio invested in equities and fixed income securities. We do not include any information about these different funds in our experiment.

Finally, the third pillar corresponds to voluntary contributions and savings. Workers may choose from a broad variety of capital market institutions and financial instruments to manage the funds corresponding to their voluntary contributions and agreed deposits. In order to complement the mandatory savings made through the AFP system, there are tax incentives to encourage people to make voluntary contributions through various financial instruments: voluntary pension savings accounts managed by the AFPs themselves, mutual funds, life insurance products with savings, etc. The scheme is designed so that savings that use these products are tax-exempt during all years in which deposits are made. The yields generated by these savings are also tax-exempt, but the pensions financed with these resources are considered as income for income-tax calculation purposes. Individuals may withdraw their voluntary savings before retirement, but they must pay the corresponding taxes and a surcharge for early withdrawal. Coverage of this pillar is very low compared to the mandatory pillar. As of June 2016, approximately 16% of the workforce had any voluntary savings accounts. Most of these accounts are opened in AFPs (70%), followed by insurance companies (12.6%) and banks (12%).

2.2 Pension savings and knowledge in Chile

Given the complexity of the Chilean pension system just described, one may wonder about Chilean individuals' financial literacy. Survey evidence about retirement planning and financial literacy in Chile shows that a large fraction of the population has low levels of financial literacy and that most of the population is not planning for retirement. For instance, results from the Social Protection Survey indicate that 82% of Chilean affiliates do not know how their pension will be calculated. Furthermore, almost half of those who claim to know about this subject give an incorrect description.[11]

The 2009 Social Protection Survey (EPS) included a financial literacy module with questions comparable to the ones analyzed in other countries (Lusardi, Michaud and Mitchell, 2011). Based on this data, Moure (2016) shows that, relative to respondents from developed countries, Chileans show lower levels of financial literacy. Less than half of respondents answer correctly a simple question about compound interest and risk, while less than 20% answer correctly a question about inflation. Moreover, the correct response rates are positively related to educational attainment and negatively related to age, and are lower for female and lower income respondents (see Hastings and Mitchell, 2010). According to this data, Chileans also show poor financial planning practices, less than 10% of the EPS sample take active planning actions, and within different subgroups of the population only individuals with post-graduate education have a planning prevalence higher than just 30%.

[11] Lack of knowledge about the system is general, most individuals do not understand or do not know basic characteristics of the system. For more details on the results from the Social Protection Survey see the evidence showed in Berstein et al. (2010).

2.3 Forecasting Pensions and Information Initiatives

The Personalized Pension Forecast Given this low level of pension knowledge, SdP has had a strategy of improving pension knowledge among the population. An important element in this strategy is the provision of a personalized pension forecast (PPP in Spanish). Since 2005, together with the last quarterly AFP statement, individuals receive a PPP whose content varies according to how far from the legal retirement age each individual is.[12] Everyone's PPP report, except those aged 20-30, also includes reminders about voluntary savings within the pension system and that they should inform themselves of the requirements to access the basic pension.

Even though the 2009 EPS shows that only 2.7% of the individuals declare looking at content other than account balance, returns or fees charged, there is some evidence the PPP (or the letter itself) have some impact on people's decisions. Using non-experimental methods, (Fajnzylber and Reyes, 2015) report a 1.4% increase in the probability of making voluntary contributions in the 40-50 age group and Miranda Pinto (2013) finds a decrease of 11% to 29% in the probability of retiring for individuals who receive the PPP. Thus, information might have an impact on people's decision, at least among those treated.[13]

The Online Simulator In order to provide better risk-related information to affiliates, the SdP built a pension simulator.[14] However, this simulator is complex to use and a limited number of individuals have accessed. We now summarize the simulators' main elements since we employed a simplified version of it in our experiment.[15]

The SdP simulator is based on a model that uses a representative affiliates' characteristics: age; gender; level and density of contributions; level of income prior to retirement; retirement age; investment strategy; and beneficiaries' number and characteristics. This model is described in detail in Berstein et al. (2013). With information about the current balances in mandatory and voluntary pension savings, the model constructs a consolidated balance. Starting from the affiliate's current age, pension savings growth is driven by monthly contributions (mandatory and voluntary savings), and by the return earned on previously accumulated pension savings.

The model assumes that funds' returns evolve stochastically over time according to a random

[12] Individuals aged 20-30 receive a reminder of how important it is to save early in order to accumulate a larger fund by the retirement age; individuals older than 30 but 10 or more years away from retirement age receive a pension forecast based on two scenarios, one in which they no longer contribute and another in which they continue contributing into their mandatory account at the current contribution level; and those within 10 years of the retirement age receive an estimated pension if they were to retire at the legal age or three years later.

[13] As (Fajnzylber and Reyes, 2015) points out, however, their identification strategy implies that the effects reported are appropriate for the treated individuals only (i.e. they correspond to treatment-on-the-treated effects rather than average-treatment-effects).

[14] Since September 2012, this simulator is available on the SdP website http://www.spensiones.cl/apps/simuladorPensiones/.

[15] This description of the simulator is based on Antolin and Fuentes (2012)

walk, where the possibility of the occurrence of crisis is considered by means of a jump diffusion process.[16] Appendix Table A.1 shows the real returns and standard deviations for each of the five types of funds and the annuities' implicit rate. These values are obtained after simulating 40 years of monthly returns.

The simulator feeds from current and projected information about affiliates. Current age, gender, current balance in the mandatory personal pension account, monthly gross income, historic average density of contributions, value of recognition bonds (these bonds are held by affiliates who made contributions in the old defined benefit Chilean Pension System), and current type of fund are obtained from administrative records.[17]

In the online version of the simulator, users are asked about their desired monthly pension upon retirement, as well as the current balance in any other type of voluntary pension-saving vehicles. Afterward, users are asked about their preferences regarding age of retirement (under current Chilean legislation, the legal age of retirement is 65 years for males and 60 for females). Users can choose to simulate delaying or anticipating this age. Users can also choose an investment strategy by selecting the type of fund (A through E) or they can select a default strategy.

In order to forecast future mandatory contributions a series of assumptions are made. Firstly, for the one-year contribution forecast, the simulator feeds on the current month taxable income and uses the current taxable income ceiling.[18] For the next years' forecasts, the Simulator assumes that this ceiling increases 1.75% each year[19]. Secondly, the gaps in contributions are assumed to be uniformly distributed. This is, if the user expects to work 6 months a year, the contribution density is set equal to 0.5 (50%). This factor is applied to the contributions made every month for the entire forecasting horizon. Regarding the values of future voluntary pension savings, the simulator assumes that these savings are invested in the same type of funds as the mandatory account. Moreover, voluntary pension savings has a monthly ceiling of UF 50. This is the current voluntary savings ceiling that is considered to give affiliates tax incentives. Finally, the simulator assumes that the future density of contributions affects the amount of voluntary savings when these savings are expressed as a percentage of the user's monthly income, but the density has no effect when future voluntary savings are expressed in pesos or UF.

The last input required is information regarding expected beneficiaries at the age of retirement. This is necessary because, under Chilean legislation, the pension to be received by the beneficiary depends on the existence and age of spouse, children entitled to pensions, and any other individual with legal rights to receive a survivor pension (this includes, for instance, children older than 24 with some degree of disability). The Simulator allows for an important degree of flexibility in

[16] The details of the stochastic process are discussed in Berstein et al. (2013).

[17] The users may also input this information manually when using the full online version.

[18] This income ceiling was equal to UF 67.4 during 2012 and 70.3 UF for 2013. The UF is an inflation-linked unit of account approximately equal to USD 48.

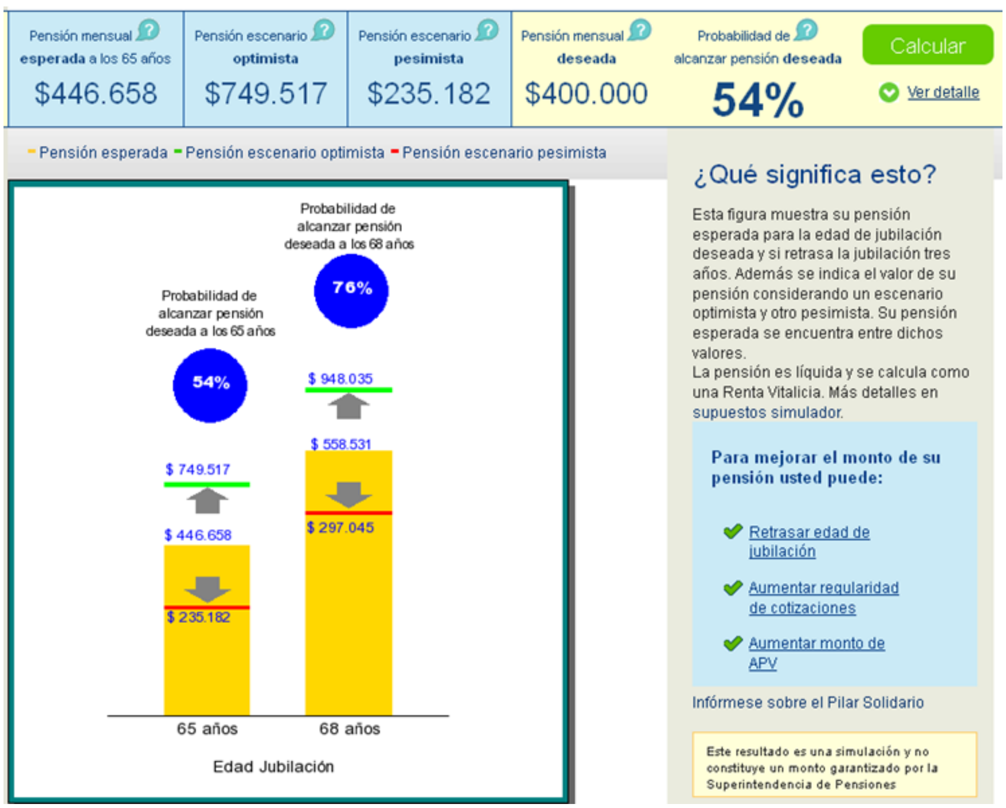
[19] The ceiling is increased every year according to the previous year change in real wages for the Chilean economy.

terms of the number and type of beneficiaries that are considered.

Using all these inputs, the simulator produces a forecast which corresponds to net pension values. In order to reach these values, the Simulator uses all the inputs provided by users to obtain 2,000 different simulations for the gross pensions.[20] A 7% health contribution is then deducted from the gross pension. The resulting value is assumed to be the only income source for users. Therefore, the currently valid income tax rates are used to obtain the net pension values.

Figure 1 shows the results given by the Simulator. The output consists of: expected pension at the age of retirement, pension payment for the 5th percentile (called "pessimistic scenario pension"), pension payment for the 95th percentile (called "optimistic scenario pension"), and the probability of having a pension payment that is equal or greater than the desired pension specified by the user. Also, users are showed the same set of results that would be obtained if they postpone the retirement age by three years.

Figure 1. Example of the SdP's Online Simulator Output



Source: Berstein et al. (2013).

[20]The mortality tables used to estimate pensions are the currently valid tables (RV - 2009 H and RV - 2009 M), which are available at http://www.spensiones.cl/files/normativa/circulares/CAFP1679.pdf.

2.4 The Experiments' (Simplified) Simulator

The pension simulator developed for the experiment is a simplified version of the SdP pension simulator. It uses administrative records, as well as information provided by participants, to project pension-savings growth and the expected value of the pension. The estimated pension are presented in current Chilean pesos, and correspond to the after-tax pensions that could be funded with an annuity.

In order to estimate expected pensions, the following simplifying assumptions are made:

1. **Investment strategy**: It is assumed that the user will follow the default investment strategy. This is, pension savings are reassigned from Fund B to Fund D as the user ages. The same investment strategy is applied to the mandatory and voluntary pension saving accounts.
2. **Pension fund returns**: Regarding the returns earned by pension savings, the methodology used replicates the one employed by the SdP pension simulator. This is, stochastic returns are estimated. A total of 2,000 monthly series of returns are built for each type of funds and for the implicit interest rates of annuities. The average annualized real returns for each fund are: 6.04% (Fund A); 5.2% (Fund B); 4.71% (Fund C); 4.35% (Fund D); 3.71% (Fund E). The average annuity rate is 3.58%. With these returns and annuity rates, a total of 2,000 pensions are calculated. The simulator reports the average pension to users.
3. **Beneficiaries**: For male users, the simulator assumes the existence of a two-years-younger spouse and that there are no children. For female users, the no-children assumption is maintained and a two-years-older spouse is considered.
4. **Density of contributions**: The simulator assumes that the future value of this variable will equal the average density of the past twelve months before the time of use.
5. **Taxable income by age group**: This variable is estimated using the users' current taxable income as baseline.[21] This figure is then increased each year. Appendix Table A.2 shows the annual growth rates for different age and gender groups. These were estimated using administrative records for members of the pension system.
6. **Taxable income ceiling**: The cap for monthly taxable income is set at UF 72.3 (CLP 1,863,677 or USD 3,170). Thereafter, the ceiling is increased at an annual rate of 1.75%.
7. **Mortality**: The RV-2009 H and RV-2009 M mortality tables are used to estimate pensions.
8. **Retirement age**: For users that are at least two years younger that the legal retirement age (65 years for males and 60 years for females), the simulator assumes that users retire at said moment. For users that are older, the simulator assumes that retirement takes place in two more years or at age 70, whichever is lower.

[21]Specifically, the simulator feeds from the users' taxable income as showed in the administrative data at the time of the intervention. There is a delay of approximately two months in this data. For instance, if an individual used the simulator during December 2015, the taxable income used would correspond to October 2015.

3 Conceptual Framework, Data and Methodology

Having described how the simulator was programmed, we now motivate the design of the experiment we implemented as well as the empirical methodology and data we will use to analyze its impact.

3.1 Conceptual Framework and Expected Outcomes

In general terms, our intervention falls in the category of providing individuals with information about the impact of their decisions on expected pensions. A relevant way in which we are able to measure the impact of this information lies in the fact that we directly ask participants' expectations regarding their future pensions. This enables us to measure differences in response according the degree in which the projections provided are (mis)aligned from expectations. The importance of measuring these expectations is that, even tough our initial guess is that individuals under-save for their retirement, it is still possible that this is not the case for all participants. This could make a difference in terms of the effect that our intervention has on saving and working patterns.

We hypothesize that providing personalized information to individuals will indicate them whether they are saving enough or if they are under or over saving (in relation to their own expectations regarding their future pension). In turn, this should lead to a change in behavior to modify formalization of their employment, retirement age and voluntary contributions to their pension fund. We expect that sign of the effects on these variables will be correlated to the degree of under/over saving for each individual.

Some discussion is required in order to clarify the degree in which modifying these outcomes is costly for affiliates. Regarding mandatory savings, in principle, every worker in the formal sector of the economy (i.e. individuals that have a working contract with a firm) are obliged to contribute 10% of their wage into their pension savings account. In practice, however, it could be possible (and anecdotal evidence suggest that this is the case sometimes) to elude this obligation. For instance, workers can be employed without a contract, and thus lowering the frequency of mandatory contributions, and can sub-report the wage received, thus effectively saving less than 10% of wages. As it was shown in Section (2.1), the mandatory savings pillar covers around 79% of working-age population, which is a high degree of coverage. Moreover, ending practices such as working without a contract and under-reporting wages requires both the initiative of workers plus an agreement with employers. These elements makes us believe that mandatory savings outcomes will be more difficult to alter. We will measure labor supply through administrative data related to mandatory contributions but also through our survey since we do not observe workers without a contract in the administrative data.

The second group of outcomes we study are related to voluntary savings. As explained earlier, only 16% of workers contribute to the voluntary pillar. In this sense, the room for impact for our intervention in these outcomes is considerably larger than for mandatory savings. Moreover, increasing voluntary savings, while implying a sacrifice in terms of current consumption, is a decision that is made by the employee alone (i.e. employers are not required to agree), and these savings can be managed by multiple types of firms. It is worth noting that voluntary pension savings are encouraged through a tax credit. However, workers with a monthly taxable income below $ 630,000 are subject to a 0% marginal income tax. As we will see in the following section, this figure is approximately 30% above the mean wage in our sample. Therefore, most of our sample may not perceive a great tax advantage of making voluntary contributions thus making the perception of future benefits from this saving behavior key in fostering the practice.

The final main outcome of interest is the decision to retire. The legal retirement age is 65 (60) years for males (females). Nevertheless, individuals that fulfill some requirements may be eligible for early retirement. Basically, the conditions to retire early state that the pension obtained is higher than 50% of the average taxable income in the last 10 years, and it should also be higher tan 110% of the State-defined minimum pension guaranteed.

3.2 Randomized Control Trial

To test these hypotheses, we implemented a randomized control trial. The intervention consisted in installing self-service modules, equipped with the pension simulation software described above in locations with a high flow of low- to middle-income but working individuals. We decided to install these modules in the locations where social payments and services targeted to their needs are delivered. In Chile, those services have been agglomerated into offices of a government office called "Chile Atiende", of which there are 153 locations across the country, receiving on average 37,000 visits per year. Most of the proceedings, inquiries or consultations performed in these offices are related to pensions (26%), information on procedures and benefits (23%), certificates (11%) and buying state-run FONASA "bonos" with which to pay medical care by a doctor (8%). A quarter of visitors wish to ask general questions or obtain information about some specific topic.

We chose to partner with this government office because the demographics of their population appeared to match that of our target population. According to the information they provided us for visits in 2013, most users are women (67%), 27% are under 40 years old, 27% between 40 and 55 years old, 24% between 56 and 65 years old and 22% with ages above 65 years old. With regard to educational level, 48% of them have primary education or incomplete secondary education, 33% completed secondary education and only 19% have complete or incomplete tertiary education.

The module was identified as a module from the SdP in order to increase its credibility. As individuals approached the module, they were asked to place their national ID card under a scanner and their index finger on a fingerprint reader. This was required for us to be able to obtain their data from the database of SdP (if they had ever affiliated to the system). They were then asked to provide consent. At that point, not only the SdP appeared as participating in the project but also the universities of the researchers and J-PAL. If they consented, they were asked to answer a short survey of about 10 minutes. Once the survey was completed, treatment individuals were led to the simulator while control participants were offered 3 simple tips to increase their pension. They were reminded that by increasing the number of times one contributes during the year, by making voluntary contributions and by delaying retirement age, one can increase their pension savings. They were given the average impact that these measures can have on a typical pension, all in percentage terms. Figure 2 shows the exact screen the control group would face. The participant had the option of obtaining a printed version of this reminder if they chose to do so. They can also have it sent to them by email.

On the other hand, treated individuals were given an estimate of their current pension based on the simulator and the exact impact that each of the three measures mentioned to the control group would have on one's pension. Figure 3 shows the screen that would appear to a given individual. That individual was anticipated to receive a pension of 130,795 Chilean pesos or about US$250 per month at the exchange rate of that year. While low, this is about 50% more than the guaranteed pension offered by the Government. This woman, in the past, has only contributed to the pension fund an average of 5 months per year.[22] The simulator shows her that by increasing the frequency of her contributions to all months of the year, she could more than double her pension. It also shows her that by voluntarily saving an extra 1% of her monthly income in an individual voluntary savings account she could increase her pension by about 15%. Finally, delaying her retirement age by 1 year would increase her pension by a bit less than 10%. All these estimates are provided for each person using her own data as available in the system. They are also expressed in terms of monetary value which may be simpler for individuals to grasp than percentages. Once at that point, the person can obtain a printed or email version of the estimates. She can also go back and alter the parameters of the simulation to see the impact of other alternatives. For example, they could try to increase the amount of the voluntary savings, alter the retirement age by more than what the system suggested or increase only partially the density of mandatory contributions. The system records those simulations for any individual who chose to do that.[23]

At first, we implemented our modules as self-serving kiosks in 8 locations of "Chile Atiende" in the metropolitan region of Santiago and its rural surroundings. The locations were selected based on the demographics of the visitors they would received, the flow of visits they had, a representativeness of rural/urban areas and geographic proximity. We ran the experiment like this for 2 months. However, the flow of individuals completing the process was very small. In partic-

[22]We know she is a woman because the assumed retirement age is 60 years.
[23]Few individuals pursued that option which is why we do not explore this data in more details.

ular, most individuals were stopping at the point where the national ID card and the fingerprint reader were required. Observational data suggested that this step was complicated for many users who would get frustrated by the process. We thus altered our implementation and randomly assigned to locations and days a module "assistant" who both encouraged participation and helped the person navigate the module. The assistants were undergraduate students who were given a basic training on the pension system. The presence of these assistants substantially raised the take-up of the module: more than 93 percent of our sample completed the experiment with an assistant, implying that our experiment should be thought of including the interaction with the assistant. However, the interaction with the assistant was the same whether the individual was in the control or the treatment group. We thus continue to highlight the fact that our experiment really contrasts the role of personalized versus generic information.

3.3 Data

The data in this paper comes from 3 separate sources. First, individuals answered a short survey when they first access the module. This survey included questions about current labor supply, education and position within the household. For individuals who were not registered in the pension system, we also included questions regarding their gender, their age and their labor earnings since we could not rely on the information provided by the SdP regarding these variables. We also requested information regarding the importance of the pension system for their retirement financing and the amount of savings they had outside the pension system. We then measured their financial knowledge using the 3 typical questions in this literature (see Hill, 2014; Lusardi et al., 2011; van Rooij, Lusardi and Alessie, 2011): present value, compound interest and inflation. We also tested their knowledge of the pension system in Chile. Finally, we also elicited their expected and desired pension levels.

The second source of data we obtained for this project comes directly from the administrative database of the SdP. This database is constructed from the information that each AFP provides to the SdP about its affiliates. Information regarding their age and gender is available, among the few demographics the database records. However, the database offers a rich set of information regarding the formal labor market participation of individuals (since all formal employed workers are required to contribute to the pension fund system), their pension savings, whether they work as employed or self-employed and whether they have retired. Finally, the database also records some information regarding the involvement of the individual in their investment decisions: whether they have asked or changed their password required to access their AFP's website, whether they have changed their savings between type of funds and whether they have changed AFPs.

We then complemented this data using a phone survey conducted around 10 months after the use of the module. Phone calls were made at the number the individuals reported as their contact information in the module as well as the phone numbers they had on file in SPD's administrative data. In this relatively short phone survey, we focused on variables that are invisible to us in administrative data. We measure informal labor force participation, savings outside the pension system and knowledge, intentions and perceptions regarding that system.

We first present some baseline information regarding the participants in our experiment. First and foremost, our strategy of simplifying the simulator and bringing it to a location where low-income individuals are more prevalent helped the population of our experiment be relatively close demographically to that of all affiliates to the pension fund system. While only 30% of those who used the simulator in its complex version online were women, roughly 52% of our participants were women, much closer to the 47% of affiliates they represent in Chile's DC system (Table A.3). Our participants also match almost perfectly the age distribution of all affiliates while those visiting the online simulator tend to be older.

As can be seen in Table 1, in terms of socioeconomic characteristics, most have at least a high school diploma and almost a third has some post-secondary education. About 12% have completed a university degree and a similar fraction did not finish high school. Two-thirds of participants are heads of household, 80% are currently working and 89% are in the labor force. They earn on average a wage of about CLP$464,000 per month, which is almost twice the full-time minimum wage in Chile. Thus, our participants are not very poor but more representative of low- to medium-income workers in the region of Santiago. Once more, however, this is much lower than online users of the pension simulator.

Almost all (95%) of our participants are affiliated to a pension fund. Most of them (83%) consider the pension system as an important source of revenue for their retirement. On average, individuals expect to receive about 58% of their current wage as a pension and wished they could receive about 15% more than their current wage as pension. On average, they contribute to the mandatory system about 8 months per year, have about 10 million Chilean pesos in their mandatory pension savings account and less than 2.5 million savings outside the pension system.

We then turn to their financial knowledge. Fewer than half can properly answer a multiple choice question regarding how pensions are calculated and also fewer than half correctly answered that 10% to 12% of one's income is contributed to the AFP (since each pension fund manager sets its own service fee on top of the mandatory savings of 10%). The participants on average answer about half of our financial literacy quiz properly and they give themselves an average score of 4.7 out of 7 in their ease with the system self-evaluation.

Regarding the frequency and magnitude of voluntary contributions, on average, participants contribute 0.4 times per year (this is, less than one month per year). For those who make voluntary contributions, the average amount represents roughly between 4% and 6% of their monthly wage. More striking, only around 5% has ever made at least one voluntary contribution.

Next, we note that the average pension we simulated for these individuals is on average marginally *larger* than the one the individuals themselves predicted. However, it could still be possible that different individuals received a simulation above (below) the ones they expected. In turn, receiving this good (bad) news may affect their behavior in different ways. In order to explore the possibility that different types of news affected individuals in a heterogenous way, we define the error as:

$$Error = \frac{Simulated\ \ Pension - Expected\ \ Pension}{(Expected\ \ Pension + Simulated\ \ Pension)} \tag{1}$$

Figure 4 shows the distribution of this variable and it suggests that, while individuals do make mistakes in how they estimate their pension, there is no sense in which they systematically over- or under-estimate their pension since the distribution is almost centered at 0. When we examine the error measured in Chilean pesos, we find that the average error is relatively small compared to the amount of the pension. The average absolute value of the error, however, is relatively large, amounting to about 66 percent of the predicted pension. This suggests that while there is no strong systematic bias in the direction of the mistake, some individuals have a very incorrect estimate of what their future pension is likely to be. We will exploit this heterogeneity later in our empirical analysis.

Overall, Table 1 suggests that our randomization worked relatively well. Few baseline characteristics are statistically different between the two groups. We will verify whether our results are robust to the introduction of baseline characteristics as controls.

Moreover, it is important to highlight that the baseline characteristics of key variables will tend to condition –to some degree- the magnitude of the effects that we can expect from our treatment. For instance, the high degree of participation in the system implies that finding further increases in formalization of labor can prove to be difficult. A similar reasoning applies to effects on retirement decisions, since on average individuals are around 20 years away from the legal retirement age. The variable in which there is more ample room for adjustments is voluntary savings. As we will see later, it is precisely on this last variable that we tend to find stronger results.

3.4 Empirical methodology

Randomized allocation to the treatment allows us to directly compare treated and control individuals. Therefore, we use a simple approach as specified in the following equation:

$$Y_{i,t} = \alpha + \beta T_i + \gamma Y_{i,(t-12)} + \delta X_{i,(0)} \mu_t + \epsilon \tag{2}$$

where $Y_{i,t}$ is the outcome for individual i in period t, T_i represents individual i's treatment status, $Y_{i,(t-12)}$ is the same outcome but one year before the treatment and μ_t represents exposition date fixed effects. $X_{i,(0)}$ represents baseline characteristics that we will include in some specifications as robustness checks. These controls include gender dummies, age (in years), log of baseline wage, log of estimated pension, head of household dummy, whether the individual was working in the baseline as well as dummies for educational attainment. Given that our outcome variables are, for some variables, a monetary value that is equal to 0 for many individuals, we use the inverse hyperbolic sine transformation of that variable. Results are almost identical when using the log of $1 + y$ as an alternative.

We have 12 months of administrative data after exposure for all the participants in the experiment. Our analysis will focus on changes made in that full period, and in their month-by-month dynamic, summarizing the latter in two 6 months periods, 1 to 6 months and 7 to 12 months since exposure.

Non-response in the baseline is very infrequent and only individuals who consented were randomly allocated to receive personalized or generic information so non-consent is irrelevant in the administrative data.

Attrition is not a problem in the analysis that relies on administrative data since we can capture the universe of participants and know that if they do not appear in the database, this is because they have not contributed during a given month. Furthermore, we can perfectly measure the entry and exit of individuals in the database for reasons such as death, retirement or affiliation.

Attrition in our post-exposure survey is much more severe. Quite a few respondents provided phone numbers that were incorrect or that had been disconnected by the time we tried to reach them 10 months later. This implied that we only managed to find about 40% of the individuals who were part of the initial survey.

Overall, however, there is no evidence that attrition in the survey is different depending on whether individuals received the personalized or generic information. This supports our claim that our problem with reaching participants was not linked with an unwillingness to answer but rather a problem that the phone numbers provided were not correctly entered or with too much rotation to be used 10 months later. We also find limited indication that attrition made our treatment and control group unbalanced on observables, as shown in Appendix Table A.4. Still the probability of answering the phone survey is higher for some individuals. Those who answered our surveys are more likely to be older, be head of households, working, have higher balances in their pension savings account, and consider the AFPs important for retirement than those who did not answer the survey.

4 Results

4.1 Aggregate results

We first estimate the overall impact that the experiment had on changes within the pension system. For that, we first document, in Table 2, the impact of being randomly assigned to treatment on the behavior of individuals over the 12 months following their visit to the module. Overall, we find modest changes to savings behavior, concentrated in the one variable that is possibly the easiest to change within the set of variables measured in our administrative data set.

The first two columns report the impact on voluntary savings, in frequency and amounts. We find that the number of voluntary contributions made over 12 months increased by about 0.07, from a mean of 0.381. However, the effect lacks statistical significance. We do find a positive and significant on the amount of voluntary savings, suggesting an increase of around 13% on this variable for individuals receiving the treatment.

The next two columns measure the change in mandatory contributions as a measure of formal labor force attachment. We find that our treatment reduced the number of times an individual made mandatory contribution to the pension fund, although not significantly. The amount of mandatory savings is not significantly changed. This is surprising since we hypothesized that, if anything, we would see an increase in that variable since individuals would be more likely to formalize their employment once they received the personalized information. Column (5) helps us understand the reason behind this as it regresses the probability that an individual has retired from the system in the 12 months after the visit to the module and finds that those who received personalized information were also more likely to retire, although this is only significant once we include controls. The probability raises by 1 percentage point, when the mean in the control group is only 1 percent. Panel A and B are very similar, suggesting that the inclusion of controls do not alter our conclusions, which is to be expected given the balance in the randomization.

In Appendix Table A.5, we explore whether variables that should not have been affected by our intervention were actually altered. First, we find no evidence that affiliation was increased. This is comforting as it suggests that our administrative data will not suffer from attrition. It is also consistent with the high levels of affiliation to the system we found in the baseline. We also test whether individuals took some active management decisions of their pension funds. Specifically, we measure whether the individual changed his type of fund within a given AFP, whether the individual changed AFP and whether the individual changed his password. We see no impact on any of these variables suggesting that the impact we measure did not necessarily come hand-in-hand with more involvement by the participant.

We thus observe that voluntary contributions, in amounts rather than in frequency, increased in response to personalized information. Nevertheless, voluntary contributions are, on average, less than 10 percent of mandatory contributions into the pension fund. The relative magnitudes of voluntary and mandatory contributions, thus, make total savings basically unaffected by our experiment. We also find no evidence that individuals replaced their mandatory contributions with voluntary ones since less than 0.1 percent of the sample ever contributed to the voluntary fund within 12 months without having contributed to the mandatory one as well.

We then turn to evaluate whether the results we obtain on voluntary and mandatory contributions as well as retirement are short-lived by looking separately at the impact in two sub-periods of six months each. Table 3 reports the results of those regressions. All of our previous results appear to only be statistically significantly different from 0 within the first 6 months of the visit to the module. We observe an increase of about 0.05 in the number of contributions, an increase of about 14 percent in voluntary contributions as well as an increase of about 0.8 percentage point in the probability of having retired. Not only is the statistical significance of the results altered between the two panels but the magnitudes as well. The impact on voluntary contributions and retirement rates are halved in the second half of the year after the experiment compared to the response in the first 6 months. In Appendix Table A.6, we report the results month by month and show that there was a fairly constant response across months up to 2 quarters after the experiment. However, they also suggest a fading out of the impact in months 9-11. Consistent with this, Appendix Figure A.1 shows the distribution in the number of contributions in the year following the visit to the module for the control and the treatment. We find no evidence that individuals enrolled in automatic savings program since the increase in the number of monthly payments is not only concentrated in 12 months but distributed across a number of payments frequency. When using regressions, we find that personalized information raised the probability of ever contributing by about 1 percent and that this is mostly stemming from individuals who have made more than one but less than 12 monthly contributions. This would be consistent with the evolution we observed over time where the effect appears to be partially fading.

Despite this short-lived effect, we argue that being able to increase voluntary savings by only providing personalized information is noteworthy, as previous literature such as Bhattacharya, Hackethal, Kaesler, Loos and Meyer (2012) and Madrian (2014) has noted that simply providing information or advice is not always enough for modifying savings behavior. We believe that a more permanent effect on voluntary pension savings may require providing adequate information and introducing some type of commitment device, such as the ones used by Thaler and Benartzi (2004) in their SMarT (Save More Tomorrow) program[24] or by Ashraf, Karlan and Yin (2006) [25]. Another measure that could be considered is simplifying the process for increasing savings as suggested by Beshears, Choi, Laibson and Madrian (2013).

While not presented here, we have re-simulated the pensions of our samples assuming that the

[24]Save More Tomorrow is a registered trademark from the authors.

[25]See Bryan, Karlan and Nelson (2010) for a survey on the use of commitment devices in several fields.

changes they made were either transitory or permanent. We find that despite the results we have documented previously, this translates into small impacts at the level of the estimated pension, mostly because voluntary savings are a much less relevant determinant of future pension than mandatory ones. Despite this, we do observe that if women were to maintain permanently the changes they had made in the 6 months following their visit, they would observe an increase in their pension of between 1 to 3 percent, which is sizeable. Thus, we conclude that the change in behavior we generated, while important, was concentrated in an element of pension savings that is marginal, making the impacts that these changes can have on future pensions, relatively small.

Since the impact of our intervention seems to have a non constant effect over time, we will focus the rest of our analysis with administrative data on the first 6 months after the experiment.

4.2 Understanding the channels

What led individuals to increase their voluntary savings? We first turn to answers from our survey. As we admitted before, response rates were low but we feel that we may still be able to learn about perceptions and feelings of participants through that mechanism.

We try to argue that the reason our experiment had the above impact is because it provided individuals with personalized rather than generic information. We now verify that this is the likely channel by looking at the impact the "treatment" had on knowledge and perceptions of individuals, as shown in Table 4. The first outcome of that table suggests that individuals who received the personalized information treatment were 9 percentage point more likely to remember having interacted with the module. This is a large fraction since the control average is 82 percent. We also find that the individuals were much more likely to identify their interaction with the module as involving alternatives to increase pension than general information or not remembering. Finally, they valued the information they received substantially more than those who received generic information.

We then turn to the knowledge displayed by individuals in the sample. Receiving personalized information appears to increase one's own perceived knowledge about the pension system. However, the performance of the respondents in the 4 questions we included to measure that knowledge, namely how pensions are calculated, the percentage discounted for pension, the role of voluntary savings and the retirement age for men and women, is positive but only significant for the last one. Individuals who received personalized information are also more likely to report having acquired information on the pension system but not significantly so.

Finally, the measured impact of the experiment on the valuation of the system is positive for the 3 outcomes we present and all of them are statistically significantly different from zero.

4.3 Heterogeneity of responses

We have argued so far that the response we document is the fruit of the personalization of information. However, we recognize that our two sets of information had other differences that were not related to the more individual nature of what was provided. First, one had piggy banks while the other did not. One referred to the anticipated impact in terms of percentage, the other one in terms of "pesos". To convince the reader that the effects we observed are not due to these other elements, we now evaluate whether individuals who under-, over- or rightly estimated their pension had a different result. We argue that while the response through acquiring information may be very different depending on whether how far one's estimate is from realty, the difference between piggy banks or their absence would be likely to be orthogonal to that variable.

We first must state that the estimation mistake is not orthogonal to characteristics of the individual. The average type of mistake made in the estimation appears to depend on gender, age and education. Nevertheless, in regressions not shown here, we find that the interaction with the pension mistake appears to be stronger than other types of interaction, in particular when competing in the same regression with the pension mistake. We thus feel that we are likely to capture the impact of "good news" or "bad news" and not of other characteristics of individuals.

We can observe in Figure 4 that there is heterogeneity in the type and magnitude of a mistake individuals make when forecasting their pension. Thus, we split the sample into three groups, those whose simulation was 15 percent below the sum of their expected and simulated pensions (that is to say $Error > 0.15$), those where that simulation was 15 percent above the sum of expected and simulated pensions and those whose simulation came within $\pm$ 15 percent of that value.[26] Thereafter, individuals are sorted into the groups according to whether they overestimated, underestimated or correctly anticipated their pensions.

Table 5 shows that the type of news that individuals received altered significantly their behavior. Individuals who received "good news" since they had grossly underestimated their pension actually decreased their savings within the first 6 months of their visit to our module. They do so entirely through a decrease in their contribution to the mandatory contribution, implying that they either stopped working or stopped contributing while working (by moving to a less formal type of employment). On the other hand, individuals who were told that their pension was likely to be much smaller than what they had expected were the only ones for which the visit to the module led to a statistically significant increase in voluntary pension contributions, both in numbers and amounts. In terms of magnitudes, the other groups are also, in general, showing lower impacts of personalized information. This is consistent with our hypothesis that our experiment did not simply act as a nudge but influenced the decisions of the participants through the personalized information it provided. Finally, we also find that these "overly-optimistic" individuals may also

[26] Results are qualitatively robust to alternative definitions and groupings.

have gotten discouraged by the news since they are the ones who also respond significantly to the provision of personalized information by retiring more.[27]

We also explore heterogeneity in the survey data. In Table 6, we first look at changes in behavior following the intervention. We find evidence that those who had largely overestimated their pension were more likely to contemplate altering their mandatory contributions but also less likely to postpone retirement when provided with information that was personalized. They are also, although not significantly so, more likely to inform themselves about the system but this is even stronger for those whom expectations were about right.

We then turn to self-reported savings. For those who increased their savings within the system, we find no evidence of crowd-out to savings outside the system. While not significant, the point estimate is positive. On the other hand, those who grossly underestimated their pension (and who were decreasing their savings within the pension fund) may have increased their savings outside the system.

Finally, the last part of Table 6 shows that, as in our main administrative data, we do not observe a strong labor market response due to our experiment. We find some evidence of increased formalization through the presence of health insurance and while the signs and magnitudes appear to indicate that those who had less overestimated their pension responded more, the only statistically significant coefficient is found for individuals who had a better estimation of their pension.

While not shown, we also found that individuals who had most underestimated their pension were, on the other hand, the ones to give the best evaluation to the AFPs in response to receiving personalized information.

We next turn to looking at whether the personalization of the actions that were suggested to participants played a relevant role. For this, we obtained estimates of pensions under alternative decisions for the control group and the treatment group. We then divide our population by which type of action was predicted to generate the highest increase in pension. More than half of our population was predicted to gain more from delaying retirement, about a third was shown that increasing density of contribution would be the most useful course of action while only 10 percent was given a higher estimate for increasing voluntary savings. We show the results of separate

[27] Although the increase in retirement is quantitatively small number (only 1.7% of our sample, 42 out of 2,500 individuals), these results were not expected. We find that this behavior was concentrated among those who were unemployed at the moment of their visit to the simulator and close to 37 percent of them did not have any income during the previous six months. Retiring allows them to unlock their retirement savings and does not prevent them from re-entering the labor force later on. Moreover, the treated group who retired obtained a simulated pension that was on average about $CLP200,000, which compares favorably with their average (formal) earnings in the last six months and it is equivalent to a 55% replacement rate over these average earnings (about $CLP360,000). Therefore, this group may have considered that the pension they could obtain was at an acceptable level, although well below their expectations. We believe this is a strong reality check regarding the possible effects of advising to postpone retirement when individuals may be facing high unemployment and low attachment in the labor market.

regressions for each of these groups in separate panels of Table 7. The first panel shows that the minority of our participants who could gain more from voluntary savings are exactly the group where the largest response in terms of voluntary savings occurred. Our precision is diminished by the sample size but the magnitudes are clearly largest in the first panel than in the other two. However, it is also clear that this group was more likely to decrease mandatory contributions. We are unable to obtain an estimate for the probability of retirement because there were no retirees in this sub-group. Panel B shows that those who were told that the best course of action was to increase contribution density are the only group that did not reduce mandatory contributions. Finally, the last panel shows that to the great majority to whom we suggested that delaying retirement would be the best course of action, there is an increase in retirement and through that, a fall in mandatory contributions. This may be because the benefits of delaying retirement we showed were perceived as too marginal compared to the leisure cost. Overall, we thus find some evidence that the personalization of the courses of actions played a role but less so than the updating of beliefs.

If the reason behind the pattern we document is because we provided new information to individuals and that they were able to update their priors in response to this, we may anticipate that those with less financial savviness would be the ones who would be the most impacted by the news. We explore this by looking, in Table 8 at the impact by estimation mistake and financial sector knowledge, in Panel A and by education, in Panel B.

We find evidence supporting our hypothesis in the first panel. Those with the lowest level of financial knowledge are the ones who increased the most their savings when being provided with a "bad" news and those who respond by reducing their mandatory contributions when receiving good ones. Savings and reduced contribution responses are reduced in groups with higher financial literacy.

We then turn to whether the response also depended on formal educational attainment in Panel B. We observe there a muckier pattern. Added savings appear to have not been concentrated amongst those with the lowest levels of education. However, the retirement propensity does follow this pattern. The reduced savings when faced with good news does appear to be strongest amongst those without a high school diploma. Thus, this appears to be in line with our hypothesis that the added information through personalization was most strongly responded to by individuals with lower degrees of financial literacy and overall education.

5 Conclusions

A defined contribution system requires much more understanding of financial concepts than a defined benefit one. Consequently, the availability of easily accessible information is crucial for the proper functioning of the system. In this paper, we show that individuals in a well-established system with more than 30 years of existence still have difficulty estimating how much their pension is and that providing personalized information regarding their pension can have substantial impact on their savings and retirement behavior, at least in the short-run, even without any additional nudges or commitment devices.

We argue that the impact of our experiment is mostly, if not entirely, due to the personalization of information and not to other behavioral responses generated by our set-up. This is because we made the personalized information as similar as possible to the generic one in terms of presentation. Furthermore, the size and importance of the impact of personalized information differed significantly depending on the type of "news" that the personalized information provided users and less so on other socio-economic characteristics. We thus see this paper as a demonstration that information, without nudge, may be useful in helping individuals making financial decisions, in particular when confronted with a complex system where the time horizon is particularly long.

However, our experiment also shows that personalizing information may lead some individuals to reduce their savings behavior. Whether this is something that should be encouraged depends on how rational we believe individuals to be. It does, however, point out to the need of trying to still reinforce savings motives even when individuals receive a "good news". Overall, the heterogeneous responses suggest that personalized and individual expectations should be taken into account when designing nudges and other encouragement interventions. Moreover, care should be taken in assessing the individuals' real prospects of continuing to be participating in the labor market while they delay their retirement.

Furthermore, our paper is silent about whether that nudges or commitment devices could not be added on to this set-up. We leave it to further research to explore the complementarity or substitutability between providing personalized information and offering commitment mechanisms to implement some of the decisions suggested by the personalized simulator. Nevertheless, our results suggest a lower-bound for a policy where personalized information could be bundled with additional instruments to increase future savings.

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6 Figures and Tables

Figure 2. Example of information provided to the control group

Figure 3. Example of information provided to the treatment group

Figure 4. Distribution of difference between predicted pension and expected pension

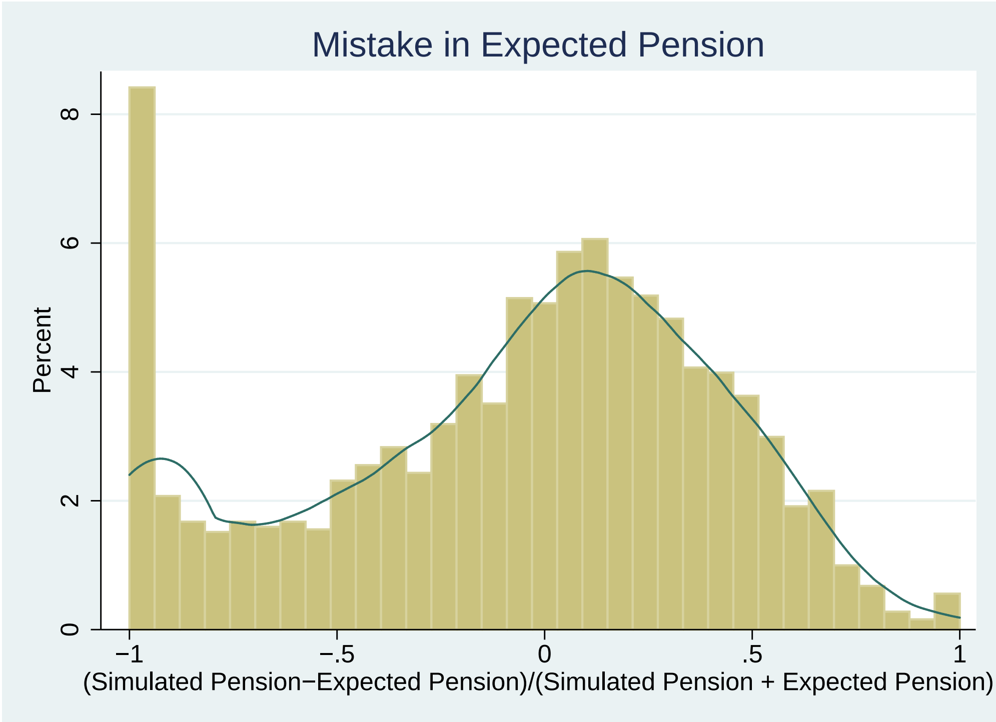

Table 1. Balance

Category	Variable	N	Mean		Difference
			Control	Treatment	T-C
Descriptive:	Female	2,545	0.510	0.526	0.020
					(0.020)
	Age	2,545	39.300	37.821	-1.414***
					(0.488)
	Primary school	2,541	0.150	0.158	0.006
					(0.014)
	High school	2,541	0.338	0.321	-0.018
					(0.019)
	Some post-secondary	2,541	0.332	0.356	0.023
					(0.019)
	Head of household	2,541	0.707	0.680	-0.024
					(0.018)
	Working	2,546	0.801	0.800	0.001
					(0.016)
	In labor force	2,546	0.905	0.883	-0.021*
					(0.012)
	Wage (avg. M$last 6 months)	2,546	446.227	481.534	39.005**
					(16.404)
Savings:	Afiliado	2,546	0.954	0.954	0.001
					(0.008)
	Desired pension (M$)	2,514	505.548	569.798	46.854
					(54.532)
	Expected pension (M$)	2,514	249.891	289.550	29.268
					(31.045)
	AFP important for retirement	2,541	0.821	0.844	0.022
					(0.015)
	Balance mandatory account (UF)	2,546	384.501	427.316	46.005*
					(27.679)
	Bono (UF)	2,546	16.337	16.081	-0.330
					(4.093)
	Savings (M$) outside system	1,598	2,781.575	2,160.213	-674.995
					(932.853)
Knowledge:	Ease with system (1-7)	2,413	4.780	4.718	-0.065
					(0.071)
	Knows how are pensions calculated	2,532	0.448	0.451	0.005
					(0.019)
	Knows % of wage discounted	2,532	0.432	0.434	0.003
					(0.020)
	Financial knowledge score (1-3)	2,535	1.566	1.574	0.014
					(0.036)
Contributions (last year):	Voluntary Cont. (M$)	2,546	19.941	30.736	10.720
					(12.747)
	Mandatory Cont. (M$)	2,546	431.733	439.042	12.232
					(19.409)
	N Voluntary Cont.	2,546	0.402	0.434	0.035
					(0.081)
	N Mandatory Cont.	2,546	7.861	8.002	0.181
					(0.190)
	Ever Contributed Vol.	2,546	0.048	0.057	0.011
					(0.009)
Simulation:	Estimated Pension (M$)	2,544	257.504	306.771	49.853***
					(12.893)
	Expected Pension (M$)	2,514	249.891	289.550	29.268
					(31.045)
	Expected Pension Mistake (%)	2,507	-0.105	-0.037	0.071***
					(0.019)
	Expected Pension Mistake (M$)	2,512	7.142	17.120	21.250
					(32.322)

Robust standard errors in parenthesis. Regressions include exposition period fixed effects.
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 2. Impact of Personalized Information on behavior within the pension system

	(1) N. of Voluntary Cont.	(2) Voluntary Savings (ihs)	(3) N. of Mandatory Cont.	(4) Mandatory Savings (ihs)	(5) Retired
			Panel A: Without Controls		
Personalized Info.	0.076	0.133*	-0.106	-0.046	0.008
	(0.050)	(0.078)	(0.133)	(0.153)	(0.005)
R^2	0.624	0.545	0.526	0.480	0.004
N	2,547	2,547	2,547	2,547	2,547
			Panel B: With Controls		
Personalized Info.	0.072	0.131*	-0.144	-0.091	0.011**
	(0.050)	(0.078)	(0.129)	(0.148)	(0.005)
R^2	0.633	0.550	0.557	0.521	0.079
N	2,536	2,536	2,536	2,536	2,536
Control Mean	0.381	0.570	7.879	10.360	0.013

Robust standard errors in parentheses. Regressions include exposition period fixed effects and controls by gender, educational level, income, simulated pension and whether the person is head of household. *** p<0.01 ** p<0.05 * p<0.1

Table 3. Impact of Personalized Information on behavior within the pension system (Months 1-6; 7-12)

	(1) N. of Voluntary Cont.	(2) Voluntary Savings (ihs)	(3) N. of Mandatory Cont.	(4) Mandatory Savings (ihs)	(5) Retired
			Panel A: Months 1-6		
Personalized Info.	0.048*	0.149**	-0.094	-0.208	0.007*
	(0.028)	(0.075)	(0.072)	(0.158)	(0.004)
R^2	0.571	0.491	0.501	0.488	0.052
			Panel B: Months 7-12		
Personalized Info.	0.028	0.083	-0.050	-0.091	0.004
	(0.029)	(0.074)	(0.077)	(0.172)	(0.003)
R^2	0.529	0.463	0.443	0.432	0.033

Robust standard errors in parentheses. Sample size is N=2,536 for each outcome. Regressions include exposition period fixed effects and controls by gender, educational level, income, simulated pension and whether the person is head of household. *** p<0.01 ** p<0.05 * p<0.1

Table 4. Impact of personalized information on knowledge and perceptions

Category	Variables	N	Control Mean	Impact of personalized info.
Recall:	Module recall	745	0.823	0.092***
				(0.025)
	Information Received:			
	Pensions, wages, etc (general)	734	0.166	-0.052**
				(0.026)
	How to increase pension	734	0.093	0.033
				(0.023)
	Module with alternatives to inc. pension	734	0.106	0.291***
				(0.030)
	Does not remember	734	0.635	-0.272***
				(0.035)
	Valuation of info received (1-7)	367	5.504	0.507***
				(0.149)
Knowledge:	Pensions system knowledge (1-7)	740	3.995	0.261**
				(0.114)
	Informed about system (last 10 months)	740	0.300	0.039
				(0.032)
	Knows how are pensions calculated	739	0.068	0.000
				(0.018)
	Knows % discounted by AFP	718	0.117	0.016
				(0.023)
	Understands voluntary savings (APV)	718	0.614	0.059*
				(0.035)
	Knows retirement age	718	0.753	0.070**
				(0.029)
AFP's valuation:	AFP qualification (1-7)	709	3.147	0.235*
				(0.133)
	Pension is an adequate retribution (0-1)	685	0.132	0.066*
				(0.035)
	Trust in the system (1-7)	719	2.834	0.225*
				(0.131)

Robust standard errors in parenthesis. Regressions include exposition period fixed effects and controls by gender, educational level, income, simulated pension and whether the person is head of household. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 5. Impact of Personalized Information on behavior within the pension system, by pension mistake, first 6 months

	(1) N. of Vol. Cont.	(2) Voluntary Savings (ihs)	(3) N. of Mandatory Cont.	(4) Mandatory Savings (ihs)	(5) Retired
Pers. Info.*	0.070**	0.215***	-0.026	-0.008	0.016**
Overest. >15%	(0.031)	(0.079)	(0.128)	(0.305)	(0.007)
Pers. Info.*	0.027	0.257	-0.080	-0.257	-0.000
Est. within 15 %	(0.063)	(0.178)	(0.142)	(0.302)	(0.010)
Pers. Info.*	0.025	-0.034	-0.211**	-0.473**	0.001
Underest. > 15%	(0.056)	(0.144)	(0.107)	(0.204)	(0.005)
R^2	0.493	0.498	0.486	0.487	0.056
Control Mean	0.189	0.466	3.998	9.380	0.009

Robust standard errors in parentheses. Sample size is N=2,507 for each outcome. Regressions include exposition period fixed effects and controls by gender, educational level, income, simulated pension and whether the person is head of household.*** $p<0.01$ ** $p<0.05$ * $p<0.1$

Table 6. Heterogeneity of responses in survey data by estimation mistake

Variables	N	Control Mean	Pers. Info. Overest. > 15%	Pers. Info. Est. within 15%	Pers. Info. Underest. > 15%
Behavior:					
During the last year considered:					
Affiliating to AFP	732	0.035	-0.032	-0.004	0.007
			(0.02)	(0.01)	(0.02)
Initializing/increasing voluntary savings	732	0.394	0.094	0.050	0.095
			(0.06)	(0.07)	(0.06)
Changing contributions frequency	732	0.159	0.117**	0.003	-0.046
			(0.05)	(0.05)	(0.05)
Changing expected retirement age	732	0.256	-0.108**	-0.024	0.020
			(0.05)	(0.06)	(0.06)
Informing more about the system	732	0.604	0.087	0.146**	-0.008
			(0.06)	(0.07)	(0.06)
Savings:					
Has other savings for retirement	717	0.202	0.045	-0.046	0.078
			(0.05)	(0.06)	(0.05)
Savings outside the system (log)	719	1.115	0.289	0.109	1.604***
			(0.46)	(0.66)	(0.55)
System's pension important (1-2)	690	0.728	-0.005	0.057	0.006
			(0.06)	(0.06)	(0.06)
Labor:					
Working	729	0.837	0.006	-0.021	-0.016
			(0.05)	(0.04)	(0.03)
Working with contract	722	0.678	-0.081	-0.020	-0.014
			(0.06)	(0.05)	(0.05)
Employed	729	0.640	-0.020	0.016	-0.046
			(0.06)	(0.06)	(0.05)
Health insurance (publ. or priv.)	725	0.870	0.063	0.056*	-0.005
			(0.05)	(0.03)	(0.03)
Public health insurance	725	0.669	0.024	0.139**	-0.055
			(0.05)	(0.05)	(0.06)
Private health insurance	725	0.202	0.039	-0.083*	0.051
			(0.03)	(0.05)	(0.05)

Table 7. Impact of Personalized Information on behavior within the pension system, by type of message, first 6 months

	(1) N. of Vol. Cont.	(2) Voluntary Savings (ihs)	(3) N. of Mandatory Cont.	(4) Mandatory Savings (ihs)	(5) Retired
	Panel A: Those who had most to gain from voluntary contributions (N=297)				
Personalized Info.	0.109*	0.218	-0.636***	-1.078***	-
	(0.063)	(0.167)	(0.183)	(0.321)	-
r2	0.182	0.257	0.296	0.333	-
	Panel B: Those who had most to gain from increasing density (N=814)				
Personalized Info.	0.035	0.129	0.047	-0.085	0.005
	(0.033)	(0.090)	(0.159)	(0.365)	(0.005)
R^2	0.144	0.131	0.243	0.249	0.079
	Panel C: Those who had most to gain from delaying retirement (N=1,294)				
Personalized Info.	0.036	0.124	-0.155**	-0.297*	0.009
	(0.048)	(0.122)	(0.077)	(0.155)	(0.007)
R^2	0.640	0.571	0.620	0.653	0.070

Robust standard errors in parentheses. Regressions include exposition period fixed effects and controls by gender, educational level, income, simulated pension and whether the person is head of household.*** p<0.01 ** p<0.05 * p<0.1

Table 8. Impact of personalized information by pension mistake and knowledge

	N. of Vol. Cont.	Voluntary Savings (ihs)	N. of Mandatory Cont.	Mandatory Savings (ihs)	Retired
			Panel A: By financial system knowledge		
Pers. Info.*Overest.	0.123*	0.430**	-0.166	-0.260	0.016
	(0.069)	(0.188)	(0.217)	(0.511)	(0.014)
Pers. Info.*Correct	-0.024	-0.018	0.096	0.129	-0.004
	(0.122)	(0.279)	(0.261)	(0.564)	(0.032)
Pers. Info.*Underest.	0.112	0.135	-0.291	-0.891**	-0.000
	(0.106)	(0.281)	(0.197)	(0.377)	(0.003)
Pers. Info.*Overest.*	-0.086	-0.371*	0.330	0.596	0.003
Medium	(0.076)	(0.197)	(0.284)	(0.678)	(0.016)
Pers. Info.*Correct*	0.029	0.002	-0.403	-0.792	0.015
Medium	(0.154)	(0.368)	(0.336)	(0.726)	(0.032)
Pers. Info.*Underest.*	-0.143	-0.146	-0.016	0.332	0.002
Medium	(0.135)	(0.360)	(0.251)	(0.479)	(0.010)
Pers. Info.*Overest.*	-0.095	-0.308	-0.032	0.025	-0.005
High	(0.073)	(0.210)	(0.367)	(0.862)	(0.020)
Pers. Info.*Correct*	0.178	1.305**	0.098	-0.022	-0.010
High	(0.171)	(0.579)	(0.370)	(0.786)	(0.035)
Pers. Info.*Underest.*	-0.097	-0.417	0.416	1.129*	0.003
High	(0.149)	(0.361)	(0.292)	(0.579)	(0.004)
			Panel B: By education level		
Pers. Info.*Overest.	0.092	0.207	-0.277	-0.827	0.049**
	(0.075)	(0.158)	(0.262)	(0.606)	(0.021)
Pers. Info.*Correct	0.146	0.168	-0.004	-0.299	0.030
	(0.149)	(0.363)	(0.376)	(0.582)	(0.055)
Pers. Info.*Underest.	-0.058	-0.192	-0.905***	-1.632***	0.002
	(0.061)	(0.172)	(0.315)	(0.576)	(0.005)
Pers. Info.*Overest.*	-0.070	-0.105	0.112	0.217	-0.049**
HSD	(0.089)	(0.230)	(0.352)	(0.802)	(0.024)
Pers. Info.*Correct*	-0.221	-0.263	-0.284	-0.180	-0.046
HSD	(0.182)	(0.450)	(0.440)	(0.745)	(0.058)
Pers. Info.*Underest.*	0.045	0.184	1.021***	1.607**	-0.006
HSD	(0.115)	(0.301)	(0.360)	(0.656)	(0.013)
Pers. Info.*Overest.*	-0.019	0.115	0.552	1.761**	-0.042*
Some college	(0.089)	(0.202)	(0.344)	(0.829)	(0.022)
Pers. Info.*Correct*	-0.178	0.013	0.036	0.057	-0.035
Some college	(0.174)	(0.474)	(0.459)	(0.829)	(0.056)
Pers. Info.*Underest.*	0.160	0.425	0.761**	1.449**	0.002
Some college	(0.105)	(0.284)	(0.366)	(0.673)	(0.007)
Pers. Info.*Overest.*	0.040	-0.019	0.192	1.050	-0.025
University	(0.107)	(0.191)	(0.430)	(0.979)	(0.027)
Pers. Info.*Correct*	0.060	0.815	0.058	0.394	-0.017
University	(0.234)	(0.623)	(0.488)	(0.941)	(0.057)
Pers. Info.*Underest.*	0.050	-0.284	0.420	0.528	0.000
University	(0.180)	(0.488)	(0.404)	(0.790)	(0.006)

Robust standard errors in parentheses. *** p<0.01 ** p<0.05 * p<0.1

A Additional Figures and Tables

Figure A.1. Distribution of number of monthly contributions in the control and treatment groups

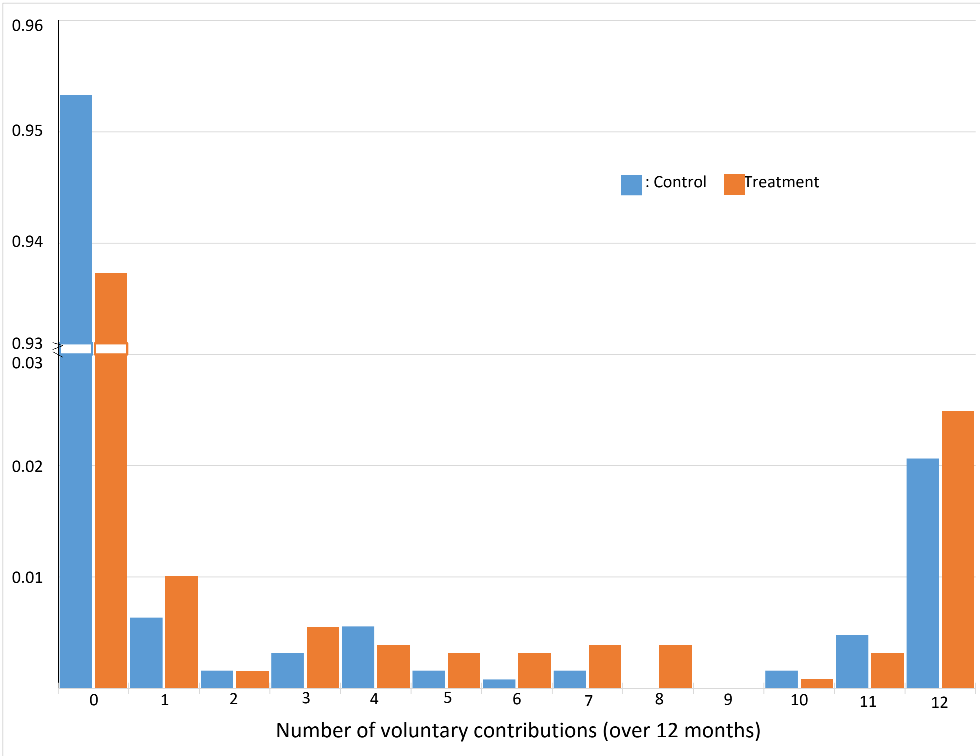

Table A.1. Simulated Real Returns (Annual %)

	Fund A	Fund B	Fund C	Fund D	Fund E	Annuities
Average Return	6.04	5.20	4.71	4.35	3.71	3.59
Standard Deviation	11.91	9.00	6.38	3.90	3.10	1.32

*Source: Berstein et al. (2013)

Table A.2. Taxable Income Growth Rate (Annual %)

Age Group (Years)	**Males**	**Females**
18 - 35	4.58	3.30
36 -55 (50*)	2.27	2.37
Over 56 (51*)	2.19	2.01

Berstein et al. (2013)

Table A.3. Participants

	All affiliates	Participants	On-line simulator
	Gender composition		
Women	46.67%	51.75%	30.64%
Men	53.33%	48.25%	69.36%
	Age composition		
Percentile 25	28	28	34
Percentile 50	38	38	48
Percentile 75	49	49	58
Average	38.92	38.94	46.20
Std. Dev.	12.51	12.84	13.16

Table A.4. Attrition

	General Info				Personalized Info						
	(1)		(2)		(3)		(4)				
	No Follow-Up		Follow-Up		No Follow-Up		Follow-Up		Diff.	Diff.	Double
	N	Mean	N	Mean	N	Mean	N	Mean	(2)- (1)	(4)- (3)	Diff.
Descriptive:											
Female	886	0.524	372	0.476	913	0.528	374	0.521	-0.033	0.005	0.039
									(0.031)	(0.031)	(0.043)
Age	886	38.512	372	41.177	913	36.257	374	41.636	2.496***	5.227***	2.749***
									(0.764)	(0.757)	(1.066)
Primary school	886	0.141	373	0.172	909	0.143	373	0.196	0.036	0.056**	0.020
									(0.023)	(0.024)	(0.033)
High school	886	0.348	373	0.316	909	0.316	373	0.335	-0.023	0.012	0.045
									(0.029)	(0.029)	(0.041)
Some post-secondary	886	0.342	373	0.308	909	0.374	373	0.311	-0.036	-0.057**	-0.029
									(0.029)	(0.029)	(0.041)
Head of household	886	0.696	373	0.732	909	0.660	373	0.729	0.037	0.079***	0.036
									(0.028)	(0.028)	(0.039)
Working	886	0.792	373	0.820	913	0.784	374	0.840	0.027	0.055**	0.031
									(0.024)	(0.024)	(0.034)
In labor force	886	0.906	373	0.903	913	0.873	374	0.909	-0.002	0.037**	0.041
									(0.018)	(0.019)	(0.026)
Wage (avg. M$last 6 months)	886	431.442	373	481.346	913	477.645	374	491.028	34.974	13.185	-24.988
									(26.176)	(25.425)	(36.424)
Savings:											
Affiliated	886	0.947	373	0.962	913	0.945	374	0.965	0.017	0.024**	0.006
									(0.012)	(0.012)	(0.017)
Desired pension (M$)	877	502.811	373	511.984	894	593.116	370	513.457	1.495	-93.946	-84.306
									(24.231)	(111.571)	(105.830)
Expected pension (M$)	877	238.915	373	275.697	894	306.759	370	247.970	29.483	-67.425	-89.842
									(23.514)	(62.831)	(62.392)
AFP important for retirement	886	0.799	373	0.874	909	0.814	373	0.917	0.066***	0.099***	0.029
									(0.022)	(0.020)	(0.029)
Balance mandatory account (UF)	885	366.662	372	429.009	913	389.000	374	520.852	39.872	117.693**	81.111
									(39.616)	(49.693)	(62.392)
Bono (UF)	886	14.819	373	19.944	913	15.587	374	17.285	3.704	-0.035	-3.225
									(7.290)	(6.404)	(9.706)
Savings (M$) outside system	606	2,892.434	192	2,431.677	606	1,784.167	194	3,334.871	-661.521	1,341.693	1,861.376
									(1,358.951)	(1,043.749)	(1,743.314)
Knowledge:											
Ease with system (1-7)	848	4.743	353	4.870	861	4.753	351	4.632	0.132	-0.116	-0.240
									(0.112)	(0.115)	(0.159)
Knows how are pensions calculated	885	0.455	373	0.432	902	0.462	372	0.422	-0.004	-0.010	-0.013
									(0.031)	(0.030)	(0.043)
Knows % of wage discounted	885	0.435	373	0.426	902	0.436	372	0.430	-0.014	-0.000	0.008
									(0.031)	(0.031)	(0.043)
Financial knowledge score (1-3)	886	1.550	373	1.603	905	1.572	371	1.577	0.051	-0.037	-0.068
									(0.057)	(0.057)	(0.080)
Contributions (last year):											
Estimated pension (M$)	885	247.180	372	282.067	913	306.364	374	307.767	27.237	-0.736	-29.088
									(17.761)	(20.877)	(27.364)
Mistake (M$) in expected pension	876	7.442	372	6.435	894	-1.461	370	62.016	-1.288	69.495	62.803
									(25.658)	(64.429)	(64.937)
Mistake (M$) (absolute value)	876	181.670	372	201.885	894	265.958	370	188.235	16.931	-83.944	-95.651
									(22.534)	(62.909)	(62.395)
Simulation:											
Estimated pension (M$)	885	247.180	372	282.067	913	306.364	374	307.767	27.237	-0.736	-29.088
									(17.761)	(20.877)	(27.364)
Mistake (M$) in expected pension	876	7.442	372	6.435	894	-1.461	370	62.016	-1.288	69.495	62.803
									(25.658)	(64.429)	(64.937)
Mistake (M$) (absolute value)	876	181.670	372	201.885	894	265.958	370	188.235	16.931	-83.944	-95.651
									(22.534)	(62.909)	(62.395)

Robust standard errors in parenthesis. Regressions include exposition period fixed effects.
*** p<0.01, **p<0.05, *p<0.1

Table A.5. Impact of Personalized Information on fund management behavior

	(1) Affiliated	(2) N. of Changes in Funds	(3) Changed AFP	(4) Active Password
	Panel A: Without Controls			
Personalized Info.	-0.003	0.022	-0.007	0.009
	(0.003)	(0.021)	(0.009)	(0.017)
R^2	0.787	0.414	0.029	0.134
N	2,546	2,546	2,546	2,546
	Panel B: With Controls			
Personalized Info.	-0.004	0.022	-0.008	0.010
	(0.003)	(0.021)	(0.009)	(0.017)
R^2	0.790	0.421	0.044	0.148
N	2,539	2,539	2,539	2,539
Control Mean	0.965	0.096	0.056	0.291

Robust standard errors in parentheses. Sample size is N=2540 for each outcome. Regressions include exposition period fixed effects and controls by gender, educational level, income, simulated pension and whether the person is head of household. *** $p<0.01$ ** $p<0.05$ * $p<0.1$

Table A.6. Impact of Personalized Information on pension savings, by month

Months since exp.	1	2	3	4	5	6	7	8	9	10	11	12
Panel A: Contributed Voluntary												
Personalized Info.	0.007*	0.004	0.005	0.006	0.008	0.005	0.009*	0.008	0.000	0.004	0.005	0.008
	(0.004)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.006)
R^2	0.715	0.621	0.593	0.574	0.553	0.542	0.516	0.489	0.468	0.477	0.477	0.448
N	2,539	2,539	2,539	2,539	2,539	2,539	2,539	2,539	2,539	2,539	2,539	2,539
ControlMean	0.033	0.033	0.030	0.030	0.029	0.033	0.030	0.029	0.035	0.033	0.033	0.031
Panel B: Log of Voluntary Contributions												
Personalized Info.	0.076*	0.049	0.057	0.084*	0.089*	0.062	0.107**	0.100*	0.023	0.056	0.060	0.080
	(0.044)	(0.047)	(0.047)	(0.048)	(0.049)	(0.052)	(0.052)	(0.052)	(0.054)	(0.054)	(0.055)	(0.056)
R^2	0.695	0.622	0.599	0.573	0.562	0.542	0.527	0.498	0.485	0.487	0.483	0.458
N	2,539	2,539	2,539	2,539	2,539	2,539	2,539	2,539	2,539	2,539	2,539	2,539
ControlMean	0.333	0.333	0.299	0.298	0.292	0.333	0.297	0.287	0.346	0.331	0.332	0.312
Panel C: Contributed Mandatory												
Personalized Info.	-0.007	-0.022	-0.019	-0.017	-0.012	-0.022	-0.012	-0.007	-0.020	-0.014	-0.006	0.000
	(0.013)	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)	(0.015)	(0.015)	(0.015)	(0.015)	(0.016)	(0.016)
R^2	0.500	0.479	0.475	0.455	0.437	0.423	0.407	0.377	0.364	0.355	0.327	0.330
N	2,539	2,539	2,539	2,539	2,539	2,539	2,539	2,539	2,539	2,539	2,539	2,539
ControlMean	0.674	0.678	0.667	0.659	0.660	0.661	0.654	0.652	0.653	0.657	0.639	0.631
Panel D: Log of Mandatory Contributions												
Personalized Info.	-0.069	-0.192	-0.186	-0.176	-0.112	-0.217	-0.153	-0.103	-0.224	-0.188	-0.054	-0.027
	(0.138)	(0.141)	(0.143)	(0.146)	(0.149)	(0.152)	(0.155)	(0.159)	(0.161)	(0.162)	(0.167)	(0.168)
R^2	0.532	0.511	0.505	0.489	0.467	0.454	0.438	0.409	0.395	0.382	0.356	0.358
N	2,539	2,539	2,539	2,539	2,539	2,539	2,539	2,539	2,539	2,539	2,539	2,539
ControlMean	7.171	7.197	7.107	7.054	7.049	7.069	7.037	7.026	7.033	7.086	6.896	6.832
Panel E: Retired												
Personalized Info.	0.004	-0.001	-0.000	0.004*	0.000	0.001	0.001	-0.001	0.001	0.002	-0.001	0.002
	(0.002)	(0.001)	(0.001)	(0.002)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.002)
R^2	0.021	0.007	0.012	0.023	0.008	0.014	0.010	0.060	0.009	0.011	0.027	0.014
N	2,539	2,539	2,539	2,539	2,539	2,539	2,539	2,539	2,539	2,539	2,539	2,539
ControlMean	0.002	0.002	0.002	0.001	0.001	0.002	0.001	0.001	0.000	0.001	0.001	0.001

Robust standard errors in parentheses. Sample size is N=2540 for each outcome. Regressions include exposition period fixed effects and controls by gender, educational level, income, simulated pension and whether the person is head of household. *** $p<0.01$ ** $p<0.05$ * $p<0.1$