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

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Abstract

We randomly offer low- to middle-income workers in Chile personalized versus generalized information regarding their pension savings. We find that personalized information, overall, increased the probability that someone would make a voluntary contribution to their pension fund in the year following the intervention and also increase the amount of voluntary savings in their pension fund, although the effect is fading out over time and is not sufficient to significantly alter future pensions. We argue that this change is due to the personalization of information and not to a general nudge since this effect is strongest for individuals who overestimated their pension at the time of the intervention. We find no evidence that savings outside the official pension system were crowded out by our intervention but found that some individuals retired more quickly after receiving personalized information. This suggests that a lack of understanding how the pension system may affect one's personal situation may explain at least part of the low contribution rates in a defined contribution system but that such information has a limited benefit without additional mechanisms to generate longer-lasting behavioral changes..

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1 Introduction

Most developing 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 pension systems instead of defined benefits ones, given their budgetary restrictions. However, defined contribution pension systems suffer from low contribution rates and low accumulation despite of its mandatory nature. Two general explanations have been provided to explain this low rate of contribution: lack of knowledge or inability to commit to savings plan. This paper focuses on the first one since it seems to be required that individuals have the right information set before we verify whether they have commitment problems. Specifically, we randomly provided *personalized information in a very concrete and simple fashion* to around 1,300 low- to middle-income individuals in Chile explaining how they could increase their expected pension. At the same time, a control group of the same size received generic information regarding how to increase their pension savings, crucially this message used no personalized information. We evaluate the impact of this information provision on pension savings using administrative data from the Chile's Superintendence of Pension (henceforth SdP, its acronym in Spanish) complemented with self-reported survey data.

Providing simple information may be relevant in the context of a defined contribution system since that type of system requires an understanding of financial concepts by the population, because the actions taken while being active in the labor market directly translate into pension replacement rates upon retirement. While individuals participating in a defined benefits system usually need only know their last x years of wage earnings to estimate their pensions, defined contribution systems rely on individuals understanding complex financial concepts such as compound interest, expected returns, market fluctuations and the timing of investments. In that context, generic advice o encourage savings such as "save today for a better retirement tomorrow" may not be fully understood by participants and thus lead to limited responses, even more when choosing a course of action requires a working knowledge of returns, contributions, and their connection to pensions at retirement.

The intervention consists of a field experiment (randomized control trial) where eight self-service modules, all equipped with a pension simulation software (Berstein, Fuentes and Villatoro, 2013), 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 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, and 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.[1]

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.[2] Such estimates are calculated using administrative data that is matched to the SdP's pensions database 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.[3] 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 is important. The control group receives *general* information and recommendations on how to improve their future pensions, including the benefits of augmenting the number of contributions per year, augmenting voluntary savings and postponing retirement age, but without any reference to their individual situation. Thus, we see that the treatment consists only in offering personalized versus generalized information, and does not focus on nudging or inducing a different behavioral response. The interest on personalized information regarding one's pension also comes from a practical point of view, as personalized messages are used around the world as many plan providers offer this type of information but its impact has not yet been tested formally in the context of a mandatory defined contribution system such as Chile's.[4]

By focusing on personalized information linking courses of action with simply explained outcomes, our intervention aims at helping individuals to 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. The main hypothesis is that the pension simulator can effectively provide information which will improve poor individuals' understanding of the role that their contributions today have on their pension levels in the future. We further hypothesize that this additional information can help individuals raise their self-funded pension by increasing formalization of their employment (through which one starts contributing to the system), through delaying retirement age (for those close to retirement age) or by making additional voluntary contributions to their pension fund (beyond the mandatory minimum).

To test these hypotheses, this project uses data from three different sources: administrative

[1] 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.

[2] Users could then request simulations with different parameters if they wished to do so.

[3] We only simulated the self-funded pension. For low-income individuals, the pension system also includes a subsidy that was not included in the calculations.

[4] Goda, Manchester and Sojourner (2014) study with a field experiment the effect of providing retirement income projections to individuals participating in employer-provided retirement accounts at the the University of Minnesota.

data obtained from the SdP, a baseline survey conducted before the simulation exercise (for the treatment group) or information provision (for the control group), 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 a bit less than one year after exposure to the self-service modules and covers topics related to their understanding of the pension system, decisions in terms of savings patterns, confidence in the system, and characteristics of the self-attention module. The intervention took place between August 2014 and February 2015 and 2,604 individuals participated, 92.8% of which were affiliated to the system by the time the intervention was conducted. 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 the treatment group compared to the control group. The estimated impact represents an increase of about 10-15 percent in terms of the voluntary savings made by participants. This is driven partly by an increase of about 1 percentage point in the number of individuals making a voluntary contribution. While small, this corresponds to an increase of around 20 percent in the fraction of individuals making these types of contributions. We also observe an increase in the probability of retiring among those in the treatment group. The increased voluntary savings are strongest for women, those with a better understanding of the system, higher educational level, or where projected to have a low replacement rate. Retirement increases are largest for close-to-retirement-age participants.

We complement these results by using data collected through a phone survey. Although our response rate is somewhat low, we find no indication in the data that the effect we documented in the administrative data was undone by savings outside the pension system. If anything, savings outside the system also appear to have increased among those treated with personalized information. We also find evidence that treatment individuals entered into more formal labor market arrangements (since their responses show they are more likely to have mandatory health insurance) and that the treatment group had more knowledge about the pension system and a more positive view of the firms that participate in the market than the control group (although this last effect is not statistically significant).

More interestingly in terms of heterogeneity, during the baseline, we elicited individuals expected pension levels and can thus differentiate the impact of the information provision by the type of "news" the individuals received from the simulation. Our increase in voluntary savings is mostly concentrated in individuals who had previously overestimated their expected pension. On the other hand, for individuals who had underestimated how much the system would provide them, we see a decrease in mandatory contributions. 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.

Chile is an interesting setting to study this question since Chile 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.

Chilean affiliates display little financial knowledge, and in particular scarce knowledge and understanding of the pension system in which they participate. The 2009 Social Protection Survey (EPS), for instance, indicates that 82% of Chilean affiliates do not know how their pension will be calculated. Moreover, almost half of those who claim to know about this subject give an incorrect description. Additionally, almost 60% of affiliates have no knowledge of either the existence of different types of pension funds nor can they explain the differences among these funds.[5] Low levels of financial literacy may be detrimental for individuals, leading to suboptimal decisions regarding which fund manager they should choose (Mitchell, Todd and Bravo, 2007) and making illiterate individuals more susceptible to the framing of the information that they receive regarding fees and returns of pension fund managers (Hastings, Mitchell and Chyn (2010)). It should be noted that the 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. These authors conclude that the degree of financial knowledge is highly correlated with the lack of skills to plan for retirement and portfolio choice as well as being substantially associated with wealth, even after controlling for the level of formal education (Behrman, Mitchell, Soo and Brava, 2012). Another important factor that influences affiliates' decisions is the existence of inertia and myopic behavior.[6] Also, 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.

Decisions of participating into the system more actively (through delaying retirement age,

[5] For more details on the results from the Social Protection Survey see the evidence showed in Berstein, Fuentes and Torrealba (2010).

[6] Inertia in individuals' investment decisions in pension plans has been documented by Madrian and Shea (2001), Agnew, Balduzzi and Sunden (2003) and Mitchell, Mottola, Utkus and Yamaguchi (2006).

formalization of employment or increasing voluntary savings) are crucial and may be difficult to understand for those with limited financial literacy. In this context, it has been shown that information plays a critical role in increasing participation into new pension plans (Duflo and Saez, 2002), delaying retirement age (Mastrobuoni, 2011; Miranda Pinto, 2012) 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.

While we are one of the first paper 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 interest rates or financial literacy on savings rate. In particular, 2 studies in 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 (see also Kast, Meier and Pomeranz, 2012, for experimental evidence about the effect of interest rates in (micro)savings in Chile). It may be that generic information is simply unlikely to change behavior.

In the Chilean context, Fajnzylber and Reyes Hartley (2015) use a natural experiment to determine the impact of personalized pension projections sent during 2005 to Chilean members of the pension system. While closely related to the topic of our study, the lack of random assignment on this work lead the the authors to employ matching techniques in order to evaluate the the effect of providing information on voluntary savings. Importantly, the authors are not able to asses if the effects found on pension savings are being compensated outside the pension system. We are able to shed some light on this issue by conducting a post-treatment survey. Moreover, our field experiment design allows us to capture a richer dimension of heterogeneity of results, such as financial financial literacy, pension system knowledge, and expectations regarding future pension which turn out to be relevant since the effect of the information we provide differs in these dimensions.

The closest paper to our research is Goda et al. (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, the use of administrative data 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". As Goda et al. (2014) can only observe the contributions through a employer-related plan in the context of the United States' Social Security system, where the amount saved would be cumulated with Social Security Savings, it is impossible for them to provide the workers an estimate of the retirement pension, thus forcing their study to focus on voluntary savings in the savings plan. In our case we provide the individuals with an expected pension, thus making the information clearer, simpler, and more informative, particularly for a group of the population with less knowledge of basic financial concepts. 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 informative. 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.

One of the main hypothesis in this paper is that information about pension savings may alter labor supply decisions, in particular the formalization of employment. This is because the pension deduction may be seen as a pure 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.

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 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 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 accounts. Reforms have been introduced 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.[7] The coverage provided by the system, measured as the proportion of members to working-age population is around 79%.

The employees' individual accounts formed with mandatory contributions can only be managed by an AFP (Pension Fund Manager of Administradora de Fondos de Pensiones). Assets under management reached USD $150,324$ million at the end of 2015 (69.1% of GDP). In return for their portofolio management services, AFPs charge a percentage of the monthly income by affiliates.[8] As part of the 2008 reform, new affiliates are assigned to the lowest charging AFP (this AFP is determined through an auction process that takes place every two years). However, after two years, affiliates can choose from one of the six AFPs currently in the market.

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. Fund A has the highest exposure to equities, with an 80% limit to invest in these securities. Fund B follows, with a

[7]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.

[8]Currently, these fees range between 0.47% and 1.54% of monthly wages. This is thus a fee defined in terms of the flow of contributions and there currently aren't additional charges on management of the stock of savings.

60% limit; Fund C has a 40% ceiling; while funds D and E have limits of 20% and 5%, respectively. For those affiliates not choosing voluntarily the destination fund for their savings, the regulation considers a default option consistent with the individual's life-cycle, i.e. the investment allocation becomes more conservative with age with shifts in portfolios smoothed over a 5 year period.

In terms of investment regulation, quantitative investment regulations apply to pension fund managers. This includes the existence of an investment policy for each fund, authorization for the investment of a significant part of pension funds abroad and the valuation of their assets at market prices using a transparent methodology.

Finally, the voluntary pillar is the last of the three fundamental pillars of the system. 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 voluntary savings accounts. Most of these accounts are opened in AFPs (70%), followed by insurance firms (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. Moreover, almost half of those who claim to know about this subject give an incorrect description. Additionally, almost 60% of affiliates have no knowledge of either the existence of different types of pension funds nor can they explain the differences among these funds.[9]

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

[9]For more details on the results from the Social Protection Survey see the evidence showed in Berstein et al. (2010).

show lower levels of financial literacy. Less than half of respondents answer correctly a simple questions 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%.

2.3 Predicting pensions

2.3.1 The Personalized Pension Projection

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 projection (PPP). 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 is each individual. 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 receive a pension projection 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. Everyone PPP annex, except those aged 20-30, also includes a reminder of the other voluntary savings vehicles available within the pension system (alternatives for voluntary savings), and that they should inform themselves of the requirements for access to the basic pension pillar.

Regarding the possible effects of the information given by the PPP, current data doesn't seem too promising. Evidence available from the 2009 EPS shows that 63% of affiliates claims having received their AFP statements in the last 12 months. This figure drops to 62% for women and to 46.8% for individuals with less than high school education.

Moreover, regarding the clarity of the information received, less than half (48%) of individuals states that this information is clear. This figure is 32%, 50% and 66% for individuals with less than high school, high school or above high school education.

While the PPP is part of the AFP statement, it is by no means the only variable included in this document. This suggests that some of the informational content provided by this projection may be lost if individuals tend to focus their attention in other contents of their statements. Indeed, individuals declare that the variables that they look in their statement are: their pension savings account balance (read by 89.5% of individuals); pension fund returns (36.4%); and fees charged (23%). Only 2.7% of individuals declare looking at other content in their statement. The PPP falls in this category.

Against the described obstacles that the PPP faces to inform affiliates, two works have found a positive effect of this information. (Fajnzylber and Reyes Hartley, 2015) reports a 1.4% increase in the probability of making voluntary contributions in the 40-50 age group and Miranda Pinto (2012) finds a decrease of 11% to 29% in the probability of retiring for individuals that receiving the PPP. A common feature of these studies is that they use the same identification strategy. Namely, a control group is constructed using individuals that didn't receive the PPP. As (Fajnzylber and Reyes Hartley, 2015) points out, however, this group was composed of individuals with high density of contributions, which 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).

2.3.2 The Online Simulator

In order to provide better risk-related information to affiliates, the SdP built a pension simulator.[10] However, this simulator is complex to use and the number of individuals who have accessed it is limited. We now summarize the simulators' main elements since we employed a simplified version of it in our experiment.[11]

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; age of retirement; 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. This sum grows during all the affiliate's active life; this is, from actual age until the age of retirement. There are two sources of growth: one is the monthly contributions made by individuals, which comes from their mandatory and voluntary savings and is affected by their density of contributions. The second one is the return earned by their existent pension savings.

The model assumes that funds returns evolve stochastically over time according to a random walk, where the possibility of the occurrence of crisis is considered by means of a jump diffusion process.[12] 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.

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

[11] This description of the Simulator is based on Antolin and Fuentes (2012)

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

The simulator feeds from current and projected information about affiliates. Several variables are filled with administrative records: 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. The users may also input this information manually.

In the online version of the simulator, users are asked about their desired monthly pension upon retirement, as well as the current balance on 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.

The next step is the definition of an investment strategy in order to specify the types of funds (A through E) in which the user plans to keep his savings until retirement. The simulator allows users to design their own investment strategy or they can also select a predefined strategy. Moreover, by selecting the advanced edition option, users can select up to two funds in which to invest their accounts.

In order to forecast future mandatory contributions a series of assumptions are made. Firstly, for the one-year contribution forecast, the simulator uses the current taxable income ceiling.[13] For the next years' forecasts, the Simulator assumes that this ceiling increases 1.75% each year[14]. 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

[13]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.

[14]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 estimate 2,000 gross pensions.[15] 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.

2.3.3 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.

[15] 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.

4. **Density of contributions**: The simulator assumes that the future value of this variable will equal the observed density at the time of use.

5. **Taxable income by age group**: This variable is estimated using the current users' taxable income and the number of years that the affiliate is in each age group. Appendix Table A.2 shows the annual growth rates for each group. 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.

3 Methodology

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

3.1 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 aim only to make general questions or to 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 university of the researchers and J-PAL. If they consented, they were asked to answer a short survey of about 10 minutes, regarding their education, labor force participation, pension knowledge, etc. For individuals not affiliated to the pension system, we would also ask them about their income since we are unable to obtain this information from the SdP database. Finally, we would conclude by asking a question regarding the value of the pension they expected to obtain when they would retire. This was asked to both control and treatment groups.

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. 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.[16] 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

[16] We know she is a woman because the assumed retirement age is 60 years.

mandatory contributions. The system records those simulations for any individual who chose to do that.

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 particular, 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. Since the assistant was such a success, we have more than 93 percent of our sample having completed the experiment with an assistant. This means that our experiment should thus be thought of including the interaction with the assistant. However, the interaction with the assistant was the same whether the individual is a control or a treatment individual. We thus continue to highlight the fact that our experiment really contrasts the role of personalized versus generic information.

3.2 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 members. 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 the administrative data of the SdP. In this relatively short phone survey, we focus 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). From those who make voluntary contributions, the average amount represents roughly between 4% and 6% of their monthly wage. A low percentage (around 5%) has ever made at least one voluntary contribution.

Finally, we note that the average pension we simulated for these individuals is on average marginally *larger* than the one the individuals themselves predicted. Figure 4 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. 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 do have a very incorrect view 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's precisely on this last variable that we tend to find stronger results.

3.3 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:

$$Y_{i,t} = \alpha + \beta T_i + \gamma Y_{i,(t-12)} + \delta X_{i,(0)} \mu_t + \epsilon \tag{1}$$

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, head of household dummy, whether the individual was working in the baseline as well as dummies for educational attainment.

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 column suggest that there is no change in the probability of being an affiliate of the pension fund system over those 12 months. However, we must remember that only 7 percent of our original sample was not affiliated, implying that there was little room for us to impact this variable.

The subsequent columns measure the impact of our intervention on savings within the pension fund. We measure the impact on total savings (voluntary plus mandatory) in the second column. Even though the impact of personalized information is negative (-2.2% without controls and -7.8% with controls), it is not statistically significant. We separate this aggregate into voluntary and mandatory contributions in the following 4 columns. We document the effect on the frequency and the amount of voluntary contributions made over the 12 months following the intervention in the next two columns. We find that the number of voluntary contributions made over 8 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 (at the 10% level) on the amount of voluntary savings, suggesting an increase of around 12% on this variable for individuals receiving the treatment.

The next two columns measure the change in mandatory contributions. We find that our treatment reduced the number of times an individual made mandatory contribution to the pension fund, although not significantly. The amount saved 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 (7) 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.

Finally, we test whether individuals took some active management decisions of their pension funds in columns (8) through (10). Specifically, we measure whether the individual changed mutual 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.

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.

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 seem to simply not have sufficient statistical power to obtain a significant impact on such a "stable" variable. 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 of the treatment for each month following the visit to the module. We present each outcome in a separate panel in Table 3. We here present only the version without controls but the results are very similar when adding controls. Panel A and B suggest that our previous results regarding increase in voluntary contribution is not driven by an immediate reaction to the module information. Coefficients suggest 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. Panel C and D continue to show negative but non-significative effects of the personalized information. Finally, Panel E suggests that the probability that a participant retires in any given month was particularly strong in the first and the fourth month after the visit to the module suggesting rather immediate decisions upon the reception of the information.

Table 4 divides our previous results into two sub-periods of six months each. 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. 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.

A long-lasting impact on voluntary contributions would be likely if our experiment led individuals to set up automatic savings programs. This is why we show, in Figure 5, the distribution in the number of contributions in the year following the visit to the module between the control and the treatment. It shows a decrease of about 2 percent in the number of individuals making no contribution during the twelve-month period and that this is shifted to a variety of frequency of payments. Individuals making monthly payments raises from about 2 percent in the control group to almost 3 percent in the treatment. However, the graph makes it clear that we did not simply increase the likelihood of a few individuals starting an automatic savings plan but rather that we also saw increases in sporadic contributions. 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.

While not presented here, we have re-simulated the pensions of our samples assuming that the changes they made were either transitory or permanent. We find that despite the sizable magnitudes of 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. We find similar magnitudes for those who had overestimated their pensions but without a statistically significant effect. Thus, we conclude that the change in behavior we generated, while important, was concentrated in a margin of pension savings that is small, making the impacts that these changes can have on future pensions, relatively small.

The richness of our administrative data has one drawback which is that it can only measure savings within the pension system. Since our experiment could very well have generated a shift from savings outside the pension system to savings inside of it, we then turn to our self-reported measures of savings from our survey. Table 5 shows various outcomes related to savings. We find that receiving personalized information regarding the pension system did increase, but not significantly so, the probability of having other savings for retirement. It did significantly increase the savings outside the system by about 80 percent. It also shows a positive but not significant impact on the probability of reporting that the pension system is relatively not important for individual's retirement. We also asked individuals to report their expected income source after retirement and found no impact of the personalized information in that regard. We also see no impact on how individuals report they plan to complement their savings after retirement. Overall, we find no evidence that the result we documented in the administrative data is likely to represent a relocation of the same savings into a different investment vehicle.

Thus, we find strong evidence that offering personalized (versus generic) information increased pension savings, at least for the part of savings that can be altered most easily. We now turn to evaluating whether other outcomes have been altered by the intervention. We first look at labor market formalization to then move to knowledge and perceptions through our survey.

Table 6 first presents various measures of labor market participation and formalization. All variables, except the last one, come from our survey measure as the administrative data measures formal labor force participation through mandatory contribution, which we have already explored previously. Given that our sample size is much smaller for the survey, this implies that we have a much diminished capacity to find a significant effect. Despite that, we seek to see whether individuals formalized their employment relationship in response to the treatment. As found previously in the administrative data, we see no evidence that individuals are working more when receiving personalized information. We also find no significant response in the probability of working for a contract or being an employee versus self-employed, as reported by respondents. However, individuals may be unwilling to reveal to us that they are working without a formal contract. Furthermore, some types of contracts are exempt from contributions to the pension fund system. To try to tease this information, we asked individuals whether they had any health insurance since health insurance contributions are made when pension fund contributions are also made. We find a significant impact on the likelihood that a participant declares having any health insurance and this is particularly strong for the publicly-funded insurance (FONASA). This suggests that, at least in the sample of survey respondents, we find evidence of higher formalization when measured through health insurance coverage. Finally, our administrative data allows us to verify the previous result on self-employment since it includes a measure of whether individuals are contributing "independently" to the pension fund, rather than through their employer. We find again no evidence that self-employment likelihood was altered by our experiment.

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 7. 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 latter. Individuals who received personalized information are also more likely to report having acquired information on the pension system but not significantly so.

When measuring intended behavior, we find that receiving personalized information decreased the likelihood that someone would think of affiliating to the system but increased their intention to make voluntary savings and informing themselves more about the system. Actual behavioral change in the survey data, however, is all not significant, maybe because of the loss of power we suffer from the lower sample size. 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 (at the 10% level).

4.2 Heterogeneity of responses

4.2.1 Heterogeneity by Demographics

Having shown that personalized information appears to have had a significant average impact on savings behavior within and outside the system, we now turn to exploring the heterogeneity in these responses. We first decompose the results by typical socioeconomic characteristics (gender, age and education level) in Table 8. Since our strongest impacts were observed in the first 6 months of the experiment, we focus solely on that window. The results are presented without the controls (except for the main effect of the interaction) and are extremely similar with and without controls. The first panel (A) shows that males and females responded in a very different way to the personalized information. Men reduced their total savings within the first 6 months of the experiment when receiving personalized information and this change is entirely due to a decrease in their frequency and amounts of mandatory contributions. The small and non-significant increases in voluntary savings is not enough to counteract this result. On the other hand, the impact of personalized information on women leads to large and statistically significant impact on the frequency and amounts of voluntary contributions. Women are also the ones who respond more strongly to the personalized information by retiring. While not shown here, the results fade out for both genders in the subsequent months but we continue to observe the gender difference in the magnitudes of the coefficients. This is relevant because women in Chile have low attachment to the labor force and their pension savings are significantly lower than those of men. Our results suggest that providing them with a personalized view of what their pension may entail is likely to stimulate their pension savings through a channel that is not necessarily linked to their labor market participation.

The next panel (B) turns to a division by age. We classify participants in 3 different groups: those more than 5 years away from retirement based on the official retirement age, those within 10 years of that age and those above the retirement age. Note that since, in Chile, retirement ages differ by gender, this implies that groups are divided based on age and gender. Also, given that we have age in the baseline only, we include men who were 64 years old and women who were 59 years old as passed the retirement age since they will cross that threshold at some point during the duration of our data. The results suggest no significant effects on any of the outcome variables for the youngest group, although all coefficients suggest increases in savings. Individuals passed the official retirement age, on the other hand, are the only group that responded to personalized information by decreasing their voluntary and mandatory contributions. It is, by far, the group for which it is the easiest to do so since, once retired, mandatory contribution is no longer "mandatory" even in the case where they continue working. Finally, personalized information appears to have induced more retirements from those who were already past the retirement age. For these individuals, our simulator showed little reward to delaying retirement age, in particular when not contributing large amounts, making this result more logical.

In the bottom panel (C), we split our sample by education levels and find no monotonic patterns. For instance, the lowest educational group without a high school degree (HSD) shows a negative and significant effect on the number of mandatory contributions as well as a large increase in the probability of retiring of 3.5% points. For the higher educational levels, we find some positive effects on number and amounts of voluntary contributions, although most of the results are not statistically significant. Overall then, there doesn't seem to be a clear trend of effects.

4.2.2 Heterogeneity by Expected Pension Mistake

More importantly, if we think that the impact of our treatment is exactly that the information is personalized, we should anticipate that individuals received different types of "shocks" depending on their previous views about their pension levels. This is what we turn next where we focus in the heterogeneity based on the difference between the expected pension and the estimated pension. Consequently, we define the error as:

$$Error = \frac{Simulated\ \ Pension - Expected\ \ Pension}{(Expected\ \ Pension + Simulated\ \ Pension)} \tag{2}$$

We can observe in Figure 4 that there is heterogeneity in this measure. Thus, we split the sample into three groups, those whose simulation was 30 percent below the average of their expected and simulated pensions, those where that simulation was 30 percent above the average of expected and simulated pensions and those whose simulation came within $\pm$ 30 percent of that value.[17] Thereafter, individuals are sorted into the groups according to whether they overestimated, underestimated or correctly anticipated their pensions.

Table 9 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

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

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

While not shown, we also explored these same types of heterogeneity in our survey data. The results show that while recall of information provided is not related to the difference between one's expected and simulated pension, the self-reported plans and decisions are. Individuals who overestimated their pension were the ones who claimed to have considered most increasing voluntary savings and changing the frequency of their mandatory payments in response to personalized information. 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 finally find that the only group where savings outside the system increased was the one who had underestimated their pension.

4.2.3 Heterogeneity by Pension and Financial Literacy

We finish our heterogeneity analysis by splitting our sample by financial literacy and by knowledge of the pension system. The idea here is that personalized information may be particularly important for individuals with the lowest degree of knowledge in terms of the pension system. However, in order to take some of the decisions studied here, one may also be able to understand the system better. We thus present, in Table 10, the heterogeneity of the impact by our measure of financial literacy, in Panel A, and by our measure of knowledge of the pension system, in the bottom panel. High financial literacy here implies having answered more than 50 percent of our questions adequately while the opposite is true for "low" financial literacy individuals. In the following panel, we divide our participants by their level of knowledge of the pension system. Individuals who answered correctly none one of our baseline questions correctly are classified as "low", those who answered one are classified as "medium" and those who answered both questions properly are classified as "high".

Overall, the results of Table 10 suggest little heterogeneity by these definitions. We find some weak evidence that those with higher financial literacy responded more strongly to the personalized information in terms of their voluntary contributions. We also observe that individuals with medium pension knowledge are the ones who retired the most in response to the receipt of personalized information. Overall, the results suggest that our difference between those who underestimated, overestimated and correctly estimated their pension is not a reflection that each of these groups has a degree of financial sophistication but instead that voluntary savings appear to have been increased by many individuals, regardless of their financial literacy or pension system knowledge.

4.2.4 Effects on Retirement Decisions

As we argued earlier in the paper, our main hypothesis is that personalized information should encourage individuals to save more and postpone retirement. The results discussed in the previous section support this hypothesis showing that the effects of personalized information on savingas have the expected sign and are statistically different from 0 in most cases. However, we also found that giving personalized information increased retirement for some individuals, namely: women, individuals near or past their retirement age, and individuals who received a pension projection below their expectations. Although the increase in retirement is quantitatively small number, only 42 out of 2,500 individuals in our sample retired (this is, 1.7% of our sample), these results were not expected, thus we further explore them in order to shade light on the possible reasons that led individuals to retire and more so after receiving personalized information.

A reasonable initial guess is that a group of treated individuals who had substantially overestimated their pension decided to retire after receiving the personalized information, most probably out of disappointment over how little they could do to alter their pension at that point. We test this hypothesis testing for heterogeneous responses of retirement along the variables mentioned above, but restricting the analysis to individuals who were 50 years and older when they received the personalized information. This allows us to verify more closely the motives for retirement, but it comes at the cost of lower statistical power.

Focusing on the restricted group of individuals, we continue to find that it is those who received bad news who were more likely to retire. But, interestingly, we also find that this behavior was concentrated among those who were unemployed at the moment of their visit to the simulator. From this point of view, the expected utility of continuing working was lower on average for the group that retired, thus making it relatively more attractive to retire. 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. Also, the decision to retire allows the person to unlock her retirement savings, thus increasing her available resources for consumption. An unemployed individual is likely to have a higher marginal utility for liquid resources, thus giving an extra motive for choosing to retire.[18]

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). Furthermore, close to 37 percent of them do not have any income during the previ-

[18] The individual can maintain her pension if she finds a job after retiring.

ous six months. This figure is not too far from the 70% replacement rate under which the Chilean pension system is often evaluated.[19] Therefore, this group may have considered that the pension they could obtain was at an acceptable level, although well below their expectations. In a certain way, they get *good* bad news about the relative benefits of retiring immediately.

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 40 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. We reminded both groups of the importance of savings and of the typical mechanisms that can be employed to increase their pension savings. 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. This is different from most interventions implemented in short-term savings systems but the personalization of the information appears to be key.

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". 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 sub-

[19] Although by its nature a DC system does not guarantee a particular pension or replacement rate, the parameters of the Chilean system (contribution rate, retirement age, etc.) were chosen expecting that individuals would obtain a 70% replacement rate upon retirement. In reality, the replacement rate has been consistently below this 70%.

stitutability 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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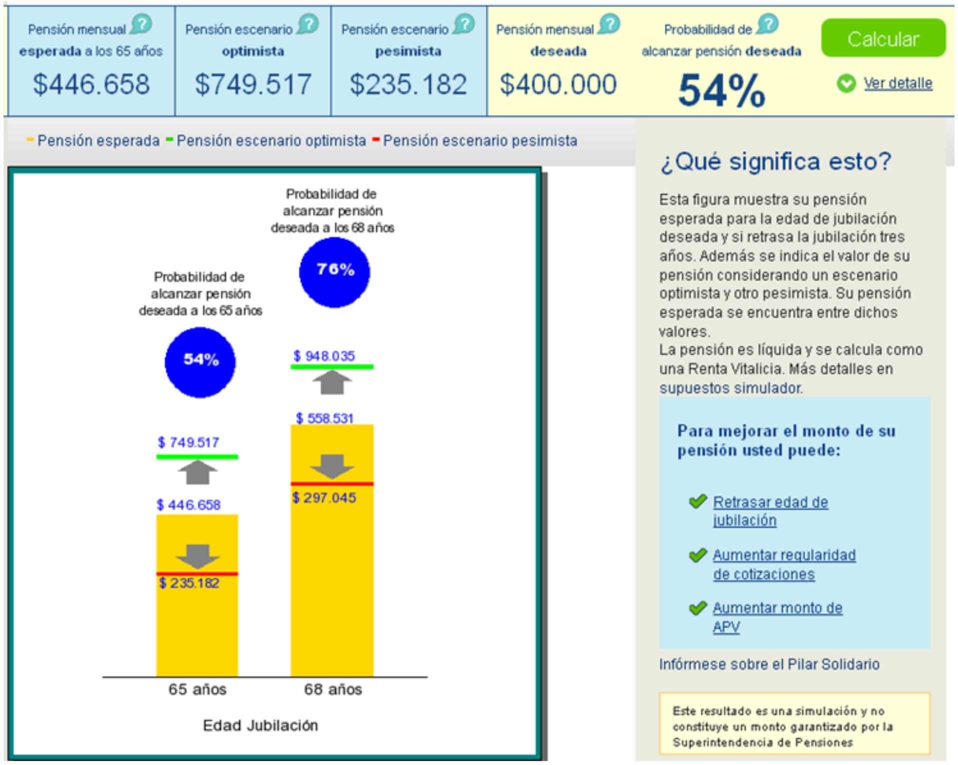
6 Figures and Tables

Figure 1. Example of SdP Simulator Output



Source: Berstein et al. (2013).

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

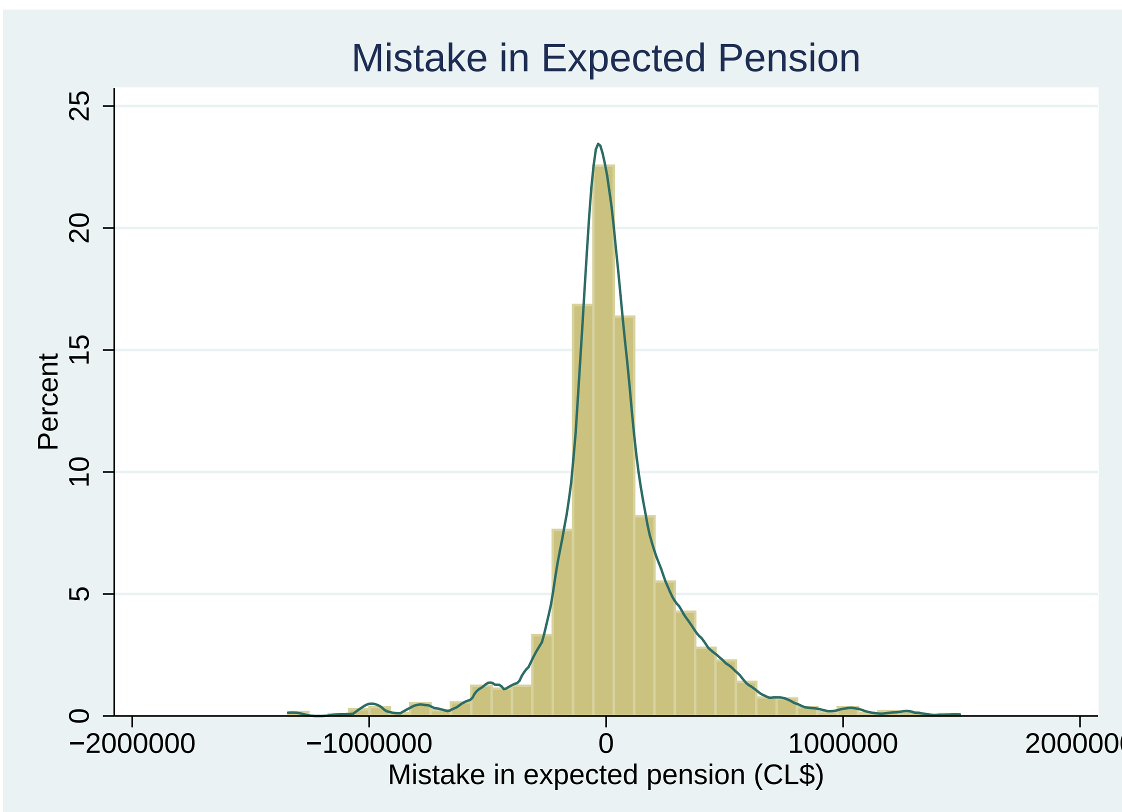


Figure 5. Distribution of number of monthly contributions in the control and treatment groups

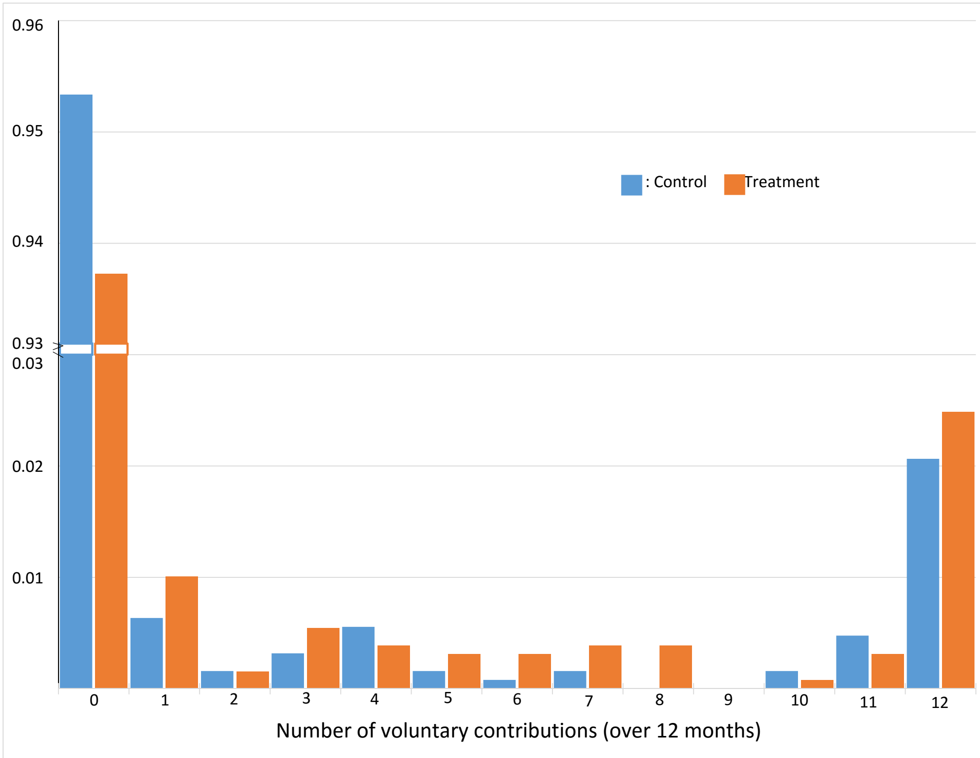


Figure 6. Distribution of difference between predicted pension and expected pension

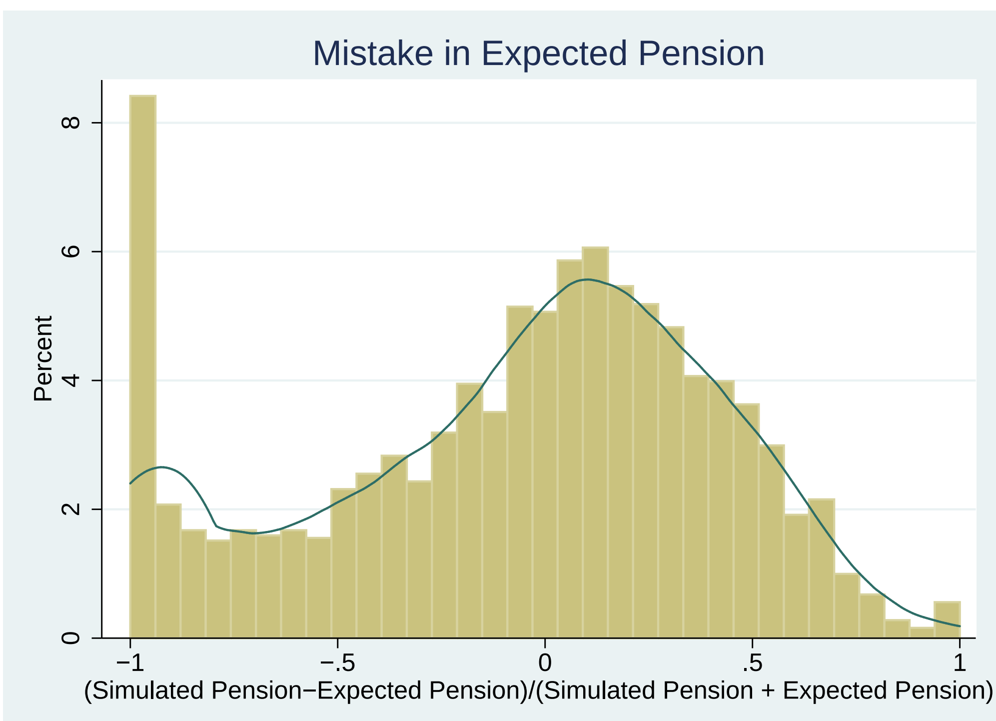


Table 1. Balance

	N	Mean Control	Mean Treatment	Difference 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$last 6 months)	2,546	446.227	481.534	39.005**
				(16.404)
Savings:				
12 Afiliado	2,546	0.954	0.954	0.001
				(0.008)
Desired pension (M$)	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$)	2,544	257.504	306.771	49.853***
				(12.893)
Mistake (M$) in expected pension	2,512	7.142	17.120	21.250
				(32.322)
Mistake (M$) (absolute value)	2,512	187.696	243.207	44.031
				(31.302)

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) Affiliated	(2) Total Savings (logs)	(3) N. of Voluntary Cont.	(4) Voluntary Savings (logs)	(5) N. of Mandatory Cont.	(6) Mandatory Savings (logs)	(7) Retired	(8) N. of Changes in Funds	(9) Changed AFP	(10) Active Password
Panel A: Without Controls										
Personalized Info.	-0.003	-0.022	0.075	0.127*	-0.108	-0.049	0.008	0.022	-0.007	0.009
	(0.003)	(0.145)	(0.050)	(0.074)	(0.133)	(0.145)	(0.005)	(0.021)	(0.009)	(0.017)
R^2	0.787	0.483	0.624	0.546	0.525	0.483	0.004	0.414	0.029	0.134
N	2,546	2,546	2,546	2,546	2,546	2,546	2,546	2,546	2,546	2,546
Panel B: With Controls										
Personalized Info.	-0.004	-0.078	0.068	0.123*	-0.157	-0.105	0.012**	0.022	-0.008	0.010
	(0.003)	(0.140)	(0.050)	(0.074)	(0.129)	(0.139)	(0.005)	(0.021)	(0.009)	(0.017)
R^2	0.790	0.522	0.634	0.554	0.557	0.523	0.082	0.421	0.044	0.148
N	2,539	2,539	2,539	2,539	2,539	2,539	2,539	2,539	2,539	2,539
Control Mean	0.965	10.392	0.381	0.570	7.886	10.369	0.013	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 3. 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

Table 4. Impact of Personalized Information on behavior within the pension system (Months 1-6; 7-12)

	(1) Affiliated	(2) Total Savings (logs)	(3) N. of Voluntary Cont.	(4) Voluntary Savings (logs)	(5) N. of Mandatory Cont.	(6) Mandatory Savings (logs)	(7) Retired	(8) N. of Changes in Funds	(9) Changed AFP	(10) Active Password
Panel A: Months 1-6										
Personalized Info.	-0.002	-0.189	0.048*	0.142**	-0.105	-0.220	0.008*	0.011	-0.004	0.016
	(0.004)	(0.149)	(0.028)	(0.070)	(0.072)	(0.149)	(0.004)	(0.013)	(0.007)	(0.016)
R^2	0.785	0.490	0.573	0.495	0.500	0.489	0.055	0.201	0.020	0.083
N	2,539	2,539	2,539	2,539	2,539	2,539	2,539	2,539	2,539	2,539
Panel B: Months 7-12										
Personalized Info.	-0.004	-0.105	0.024	0.076	-0.062	-0.119	0.004	0.019	-0.006	-0.016
	(0.003)	(0.162)	(0.029)	(0.070)	(0.077)	(0.163)	(0.003)	(0.013)	(0.006)	(0.014)
R^2	0.790	0.434	0.525	0.467	0.441	0.432	0.033	0.323	0.022	0.234
N	2,539	2,539	2,539	2,539	2,539	2,539	2,539	2,539	2,539	2,539

Robust standard errors in parentheses. Sample size is N=— for each outcome *** $p<0.01$ ** $p<0.05$ * $p<0.1$

Table 5. Impact of Personalized Information on Savings outside the pension system

Variables	N	Control Mean	Impact of personalized info.
Has other savings for retirement	725	0.203	0.031
			(0.030)
Savings outside the system (log)	727	1.128	0.764**
			(0.323)
System's pension important (1-2)	698	0.728	0.019
			(0.033)
Expected income source after retirement:			
Pension and government transfers	725	0.094	-0.009
			(0.022)
Pension and complementary sources	725	0.771	0.046
			(0.030)
Not clear	725	0.135	-0.033
			(0.024)
How to complement savings after retirement:			
Other savings	629	0.140	-0.019
			(0.027)
Keep working	629	0.733	0.020
			(0.035)
Family help	629	0.051	0.021
			(0.019)
Real estate	629	0.178	-0.030
			(0.028)
Other	629	0.016	-0.000
			(0.010)

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 6. Impact of Personalized Information on Labor market participation and formalization

Variables	N	Control Mean	Impact of personalized info.
Working	733	0.837	-0.003
			(0.023)
Working with contract	726	0.678	-0.030
			(0.030)
Employed	733	0.640	-0.009
			(0.031)
Income from main occupation	674	494,699.845	-11,771.835
			(30,226.574)
Additional income	690	42,898.150	8,728.998
			(10,164.804)
Health insurance (public or private)	729	0.870	0.040*
			(0.021)
Public health insurance	729	0.669	0.026
			(0.031)
Private health insurance	729	0.202	0.014
			(0.026)

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 7. Impact of personalized information on knowledge and perceptions

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)
Behavior:			
During the last year, considered:			
Affiliating to AFP	740	0.035	-0.011
			(0.012)
Initializing/increasing voluntary savings	740	0.395	0.080**
			(0.036)
Changing contributions frequency	740	0.159	0.020
			(0.028)
Changing expected retirement age	740	0.254	-0.038
			(0.031)
Informing more about the system	740	0.603	0.062*
			(0.036)
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 8. Impact of Personalized Information on behavior within the pension system, by demographics, first 6 months

	(1) Total Savings (logs)	(2) N. of Voluntary Cont.	(3) Voluntary Savings (logs)	(4) N. of Mandatory Cont.	(5) Mandatory Savings (logs)	(6) Retired
			Panel A: By Gender			
Pers. Info.*Male	-0.407*	0.017	0.010	-0.187*	-0.428**	0.004
	(0.217)	(0.039)	(0.101)	(0.105)	(0.217)	(0.005)
Pers. Info.*Female	0.016	0.078**	0.266***	-0.029	-0.024	0.011*
	(0.206)	(0.037)	(0.096)	(0.098)	(0.206)	(0.006)
R^2	0.490	0.573	0.496	0.500	0.489	0.056
N	2,539	2,539	2,539	2,539	2,539	2,539
			Panel B: By Age			
Pers. Info.*> 10 yrs from Retirement	1.030	0.161	0.353	0.268	0.900	0.017
	(0.821)	(0.210)	(0.741)	(0.443)	(0.838)	(0.015)
Pers. Info.*< 10 yrs	0.284	0.102	0.341	0.268	0.239	-0.006
	(0.364)	(0.086)	(0.221)	(0.166)	(0.363)	(0.005)
Pers. Info.*Passed Retirement Age	-1.146	-0.007	0.480	-0.737**	-1.154	0.168*
	(0.736)	(0.234)	(0.437)	(0.361)	(0.731)	(0.089)
r2	0.653	0.749	0.655	0.654	0.648	0.306
N	517	517	517	517	517	517
			Panel C: By Educational Level			
Pers. Info.*<HSD	-0.792**	0.068	0.095	-0.381**	-0.803**	0.035**
	(0.347)	(0.054)	(0.117)	(0.177)	(0.347)	(0.016)
Pers. Info.*HSD	-0.361	-0.017	0.001	-0.112	-0.364	-0.002
	(0.239)	(0.047)	(0.117)	(0.119)	(0.239)	(0.008)
Pers. Info.*Some college	0.294	0.062	0.253**	0.072	0.236	0.003
	(0.277)	(0.041)	(0.111)	(0.128)	(0.277)	(0.005)
Pers. Info.*University	-0.282	0.128	0.233	-0.201	-0.332	0.011*
	(0.370)	(0.093)	(0.235)	(0.173)	(0.371)	(0.007)
R^2	0.491	0.574	0.496	0.501	0.490	0.059
N	2,539	2,539	2,539	2,539	2,539	2,539
Control Mean	9.212	0.192	0.447	3.887	9.180	0.004

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

Table 9. Impact of Personalized Information on behavior within the pension system, by pension mistake, first 6 months

	(1) Total Savings (logs)	(2) N. of Voluntary Cont.	(3) Voluntary Savings (logs)	(4) N. of Mandatory Cont.	(5) Mandatory Savings (logs)	(6) Retired
Pers. Info.*Overest. Pension by more than 15 percent	0.071	0.058**	0.165**	0.006	0.040	0.017**
	(0.293)	(0.029)	(0.070)	(0.132)	(0.294)	(0.008)
Pers. Info.*Est. Pension within ± 15 percent	-0.184	0.036	0.266	-0.095	-0.255	0.003
	(0.279)	(0.066)	(0.173)	(0.139)	(0.278)	(0.011)
Pers. Info.*Underest. Pension by more than 15 percent	-0.568***	0.031	-0.002	-0.265**	-0.573***	0.000
	(0.198)	(0.053)	(0.131)	(0.106)	(0.198)	(0.004)
r2	0.488	0.575	0.497	0.497	0.487	0.059
N	2,507	2,507	2,507	2,507	2,507	2,507
Control Mean	9.393	0.189	0.466	3.998	9.380	0.009

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

Table 10. Impact of Personalized Information on behavior within the pension system, financial literacy and system knowledge

	(1) Total Savings (logs)	(2) N. of Voluntary Cont.	(3) Voluntary Savings (logs)	(4) N. of Mandatory Cont.	(5) Mandatory Savings (logs)	(6) Retired
			Panel A: By Financial Literacy			
Pers. Info.*Low	-0.221	0.043	0.092	-0.089	-0.256	0.005
	(0.206)	(0.034)	(0.090)	(0.103)	(0.206)	(0.005)
Pers. Info.*High	-0.180	0.055	0.193*	-0.132	-0.208	0.010
	(0.215)	(0.045)	(0.108)	(0.100)	(0.215)	(0.006)
R^2	0.490	0.573	0.495	0.500	0.489	0.056
N	2,539	2,539	2,539	2,539	2,539	2,539
			Panel B: By Pension System Knowledge			
Pers. Info.*Low	-0.351	0.085	0.208	-0.161	-0.384	0.006
	(0.267)	(0.053)	(0.129)	(0.128)	(0.267)	(0.009)
Pers. Info.*Medium	-0.212	0.021	0.051	-0.127	-0.225	0.012**
	(0.222)	(0.040)	(0.097)	(0.105)	(0.222)	(0.005)
Pers. Info.*High	0.116	0.051	0.239	0.052	0.048	0.000
	(0.310)	(0.053)	(0.159)	(0.150)	(0.309)	(0.006)
R^2	0.490	0.574	0.496	0.501	0.489	0.057
N	2,539	2,539	2,539	2,539	2,539	2,539
Control mean	9.393	0.189	0.466	3.998	9.380	0.009

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

A Additional Tables

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) No Follow-Up		(2) Follow-Up		(3) No Follow-Up		(4) 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