Digitalization and Retirement Contribution Behavior: Evidence from Administrative Data

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Abstract

Although digitalization promises to help individuals plan adequately for their retirement, no evidence has been provided yet on its actual impacts. Using Swiss administrative pension fund data, we document limited take-up of financial incentives for retirement contributions. Exploiting the staggered roll-out of a digital pension application across occupational pension funds over time, we show its introduction has large effects on tax-favored retirement contributions. We then leverage a field experiment to show that using the digital pension app affects retirement contribution behavior mainly through reducing the "hassle" costs of making contributions, rather than providing information on associated tax savings. (JEL C93, D14, D83, G51)

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The demographic transition has prompted the reform of the social security system in many countries, with the phase-in of defined contribution schemes that are often, at least partially, non-mandatory and tax-favoured. This ongoing process of reform is making individuals increasingly responsible for their retirement preparedness. However, a large literature has documented that many individuals take poor decisions when saving for retirement and fail to take-up the fiscal benefits they are entitled to (Madrian and Shea, 2001; Currie, 2006; Saez, 2009; Choi et al., 2011). In this context, government agencies and pension funds in several countries have introduced (e.g., the Netherlands) or plan to offer (e.g., Germany and United Kingdom) digital pension tools linked to the individuals' retirement saving accounts.[1] Digitalization promises to help individuals to plan for retirement by reducing information search costs (Goldfarb and Tucker, 2019) and the "hassle" costs from making voluntary additional contributions to the retirement accounts. While few recent studies have investigated the effect of financial incentives (Bauer et al., 2022) and tailored pension information (Dinkova et al., 2018) on the navigation behaviour in digital pension environments, no evidence has been provided yet on the effect of their introduction on retirement contribution behavior. Understanding how contributions to a retirement account respond to the availability of these digital tools is crucial not only for the design of future financial technology in support of retirement saving, but also to inform models of portfolio choice and retirement saving behavior. Based on administrative pension fund data, this paper provides first evidence on the individuals' retirement contribution response to obtaining access to a digital pension application, and on the underlying mechanisms.

Making voluntary contributions to a tax-favoured retirement saving account requires individuals to accumulate knowledge about the associated financial benefits and is relatively complex and time consuming. In the presence of significant transaction costs or costly pension-related information acquisition, individuals might find it optimal not to act (Caplin and Dean, 2015; Jappelli and Padula, 2013; Lusardi et al., 2017). We consider the introduction of a digital pension application, designed to overcome these difficulties, among individuals insureds with two Swiss occupational pension funds. The Swiss three-pillar pension system is characterised by generous financial incentives for retirement contributions. Individuals can save up to 47 percent of the present value of contributions in taxes over their lifetime, contributing the same pre-tax amount to an occupational retirement account, compared to a traditional savings account (OECD, 2018). The digital pension app is linked to the individual retirement saving account and provides detailed information to the user regarding

[1] An online platform, the "Digitale Rentenübersicht", is planned to be introduced in Germany in 2023 (German Federal Ministry of Labor and Social Affairs. 2020. "Die digitale Rentenübersicht kommt". accessed Nov 10, 2020. `https://www.bmas.de/DE/Presse/Pressemitteilungen/2020/digitale-rentenuebersicht-kommt.html`). The UK plans to introduce the "Pension Dashboard" in 2023 (Pensions Dashboard Programms. 2020. "Timeline and next steps". accessed Nov 10, 2020. `https://www.pensionsdashboardsprogramme.org.uk/timeline-next-steps/`.)

her occupational pension plan. In particular, the app allows to compute the tax savings an individual can achieve by making a voluntary contribution and to directly apply for these benefits through the pension app, greatly simplifying the contribution process. In a simple theoretical framework, we show that reducing transaction costs or misperception about the tax savings from tax-favoured contributions increases individual retirement contributions. Our main goal in this paper is twofold: (i) provide an estimate for the impact of making the pension app available to insureds on voluntary contributions to their occupational pension plans; (ii) explore the main behavioral mechanisms underlying the retirement contribution responses.

Using administrative data from two Swiss pension funds, we first document key facts about individuals' retirement preparedness and contribution behavior, with a focus on the extent with which individuals are taking advantage of the financial incentives to save for retirement brought about the Swiss pension system. The administrative data include error-free information, for the years 2013 to 2021, on insureds' annual labor income, stock of pension wealth in the occupational pension plan, tax-favoured buy-in potential, contribution decisions as well as projected pension wealth and annuities under the current contribution scenario. The sample of insureds in the two pension funds is representative of the Swiss population with respect to gender, age and income. Each year, around 3 percent of the insureds make voluntary contributions to their occupational pension plan on top of the mandatory part, with around 70 percent of insureds making at least one voluntary contribution before retirement. The additional voluntary payment is substantial, amounting to around 30'000 CHF on average. We document a substantial potential for tax-favored savings to occupational pension plans, with individuals being eligible to deduct, through making voluntary contributions, twice their annual labor income from their taxable income before the normal retirement age on average.

We then study the consequences of making the new digital pension application available on individuals' voluntary contributions to their retirement accounts. Our identification strategy for the effect of providing access to the digital pension app uses its staggered roll-out across two occupational pension funds over time. We adopt an event study design that exploits the circumstance that, while the individuals insured with one pension fund were granted access to the pension app in 2017, the individuals insured with the second fund had the possibility to access the application only in 2018. The differential timing of the introduction of the pension app across the two funds was decided by their management solely based on administrative considerations. This motivates our main identifying assumption that receiving the invitation letter in a given year is exogenous to the individual voluntary contribution to the retirement saving account, conditional on a set of determinants we control for, fund and years fixed effects. We show that the two funds insure individuals with similar characteristics and pre-treatment contribution decisions, and that contribution behavior does not respond before the pension app is introduced. Exploiting the natural experiment, we find that providing access to the digital pension app has an important effect on retirement contribution decisions. The overall probability to make a tax-favoured contribution to the occupational pension plan increases by 1.8 percentage points following the introduction of the pension app, from an average pre-treatment annual voluntary contribution rate of 2.8 percent. Using pension app registration data, we also show that the contribution response comes from those individuals who register to using the pension app (around 20 percent of insureds, in June 2019). Further, we find substantial effect heterogeneity, with contribution decisions of men, higher income earners and individuals with larger potential of tax-favoured contributions responding more to the introduction of the pension app. Men and higher income earners are also more likely to access the digital pension application. Because of the way financial incentives for retirement contributions are designed in the Swiss pension system, this evidence indicates those responding more to the introduction of the digital application are those who have more to gain, ex-ante, from making a tax-favoured contribution.

The natural experiment allows us to obtain an estimate for the intent-to-treat (ITT) effect of making the pension app available, but does not allow us to obtain an estimate for the effect of using the digital application (since whether to register is an individual choice) and is silent on the mechanisms underlying the contribution response. To provide an estimate for the causal effect of using the app, and obtain some evidence on the underlying behavioral mechanisms, we conduct a randomized field experiment among insureds who had yet to register to the pension app in the fall of 2020. We randomize the sample of non-uptakers of the pension app into a control group, not receiving a reminder invitation letter, and three treatment groups: (i) receiving a reminder with baseline information about the app content; (ii) reminder with an additional nudge towards the digital application computing the tax savings from contributions; (iii) reminder with additional nudge towards the digital application reducing the "hassle" costs of making a contribution.

We first leverage the random treatment assignment to instrument individual registration status and identify the local average treatment effect (LATE) of using the pension app on actual contribution behavior. This strategy allows us to estimate the effect of the digital app on those who registered because they received the reminder invitation letter. We show that the treatment assignment was in fact unconfounded and there is no evidence of differential attrition between treatments and control groups. Further, receiving any of the reminder letters increases the probability to register in the digital pension app by about 7 percentage points, corresponding to an almost doubling of the registration rate observed in the control group. We find that using the digital pension app increases the probability to make a voluntary retirement contribution by about 13.5 percentage points and increases the contributed amount by around 138 percent, corresponding to an increase in annual contributions to the retirement accounts of about 750 CHF.

Second, we exploit the different nudges within the letters to provide evidence on the importance of alternative barriers to tax-favoured retirement contributions. We start by estimating the ITT effect of sending a specific letter. The results show that sending the baseline reminder registration letter or the letter nudging towards the pension application computing the tax savings from contributions has no effect on actual contribution behavior. In contrast, merely receiving the letter nudging towards the digital application decreasing the "hassle" costs of making a contribution increases the probability to make a buy-in by about 1 percentage points, and the overall contributed amount by around 10 percent. We further exploit the different nudges within letters to estimate the effect of using the digital application for those individuals who registered because they received a specific letter. The results show substantial LATE heterogeneity across treatment groups, with no significant effects on actual contribution behavior of using the app among those receiving the baseline or the "tax savings" letter, and large contribution responses to using the digital application among those who registered because they were nudged towards the app simplifying the contribution process. Together, these results provide compelling evidence that the reduction in "hassle" costs of making a contribution is the main mechanism underlying the contribution response to the digital application.

This paper contributes to a recent literature that studies the role of digital pension environments on retirement-related behavior. Bauer et al. (2022) provide experimental evidence that financial incentives are more important than peer-information in motivating individuals to check their pension information. The authors find no effect on the short-term self-reported saving behavior of information uptake. Dinkova et al. (2018) focus on the role of tailored pension information based on age in explaining the navigation behavior within a digital pension environment. Senior participants are found to be more responsive to tailored pension information. We make two main contributions to this literature. First, we are the first to provide estimates for the effect of introducing a digital pension application on actual retirement contribution behavior. This is an important pension policy parameter considering the central role the process of digitalization has in the pension industry and pension policy agenda in many countries. Further, we complement the results in Bauer et al. (2022) on the importance of different barriers to retirement contributions, by using information on actual, not self-reported, contribution behavior from administrative pension fund data. While our results also show that merely providing information does not affect retirement contribution behavior, we find digitalization does affect behavior through reducing the "hassle" costs from making a contribution. Finally, using pension app registration data, we also characterize the demand for digital pension environments.

Our work is also related to the literature that studies how information treatments can overcome the factors responsible for poor decision making in retirement planning. Duflo and Saez (2003) show that standardized retirement-related information during a benefits fair increases enrollment to Tax Deferred Accounts in the US. Other studies have found mixed evidence on the effect of providing personalized information on retirement benefit projections using letters or brochures. Mastrobuoni (2011) finds that information about future social security benefits has a positive impact on knowledge but not on contribution behavior. In contrast, Goda et al. (2014) and Dolls et al. (2018) find that providing information on expected retirement benefits does affect retirement contributions. Further, Liebman and Luttmer (2015) show that an informational intervention about the incentives of social security factors has an impact on labor supply. Peer information can instead lead low-saving individuals to decrease their contributions (Beshears et al., 2015). Together, these studies show that both the type and the way in which the information is provided are key for the size and direction of the behavioral response. While previous studies mainly focused on the role of limited knowledge about expected pension benefits, we show that the introduction of the digital pension app induced a substantial retirement contribution response in a setting where individuals are already annually informed about future expected pension benefits. We also complement the evidence in (Beshears et al., 2015) about the barriers to retirement contributions of low savers, showing that the simplification of the application process for making a contribution is effective among this group of individuals.

Further, we add to the literature that considers explanations for the limited take-up of fiscal benefits (Currie, 2006; Bhargava and Manoli, 2015; Saez, 2009). We contribute to this literature in two ways. First, we document a substantial potential for tax-favoured voluntary retirement contributions in Switzerland using administrative pension fund data. Second, we show that digitalization can increase the take-up of financial incentives for retirement contributions. Finally, our results show that, in the context of tax-favoured contributions to retirement saving accounts, the “hassle” costs of making a contribution are an important determinant of the low take-up of financial benefits.

The remainder of the paper is organized as follows. In the next section, we describe the institutional setting, present the administrative pension fund data and some key facts about tax-favoured contribution potential and determinants of voluntary contributions. Section 2 describes the digital pension application and introduces the methodological approach. In Section 3 we present the natural experiment, the identification strategy and the results on the effects of introducing the digital app. Section 4 reports on the results of the field experiment. The final section discusses conclusions.

1 Institutional Setting and Data

1.1 The Swiss pension system

Switzerland's three pillar social security system combines defined benefits and defined contribution schemes.[2] The Swiss system has strong parallels to the social security system in the United State due to the combination of a capped defined benefits scheme and substantial defined contribution scheme. Contributions to all three pillars are exempt from income taxes and only taxed when paid out at retirement.

The Swiss Old Age Insurance - *first pillar* - is a pay-as-you-go re-distributive scheme aiming at securing a minimum living standard for the elderly.[3] Mandatory contributions are a fixed percentage of labor income (8.7 percent) but retirement benefits are subject to an upper limit.[4] Consequently, replacement rates are low and decreasing for individuals with higher income levels. For example, the replacement rate from the first pillar cannot exceed 28 percent for an individual earning annually 100'000 CHF.

Occupational pension plans - *second pillar* - are defined contribution schemes aiming to maintain living standards during retirement for insureds and are mandatory for employees with an income above 21'330 CHF (around 50 percent of the minimum annual wage for a full time employee).[5] The employer selects a pension provider that insures her employees.[6] The pension fund has to offer at least the minimum standards defined by the legislator.[7] Both employers' and insureds' contributions are credited to an individual retirement account within a pension fund.[8] At retirement, the accumulated capital is paid out either as a lump-sum, an annuity or a combination of the two.[9]

Private retirement accounts - *third pillar* - are special saving accounts that allow for

[2]A comprehensive description of the Swiss pension system can be found in Bütler (2016). This study focuses on employed individuals. There are different rules for self-employed individuals in place.

[3]The first pillar resembles the Old-Age, Survivors, and Disability Insurance in the US.

[4]Benefits are calculated as a combination of years of contribution and average labor income up to an upper cap. Single individuals receive not more than 2'370 CHF per month. Married couples receive not more than 3'555 CHF jointly.

[5]The occupational pension plans show similarities to the 401(k) plans in the United States.

[6]Switzerland had 1'643 pension funds in 2017 that managed 894.3 billion CHF in assets which is corresponding to about 133 percent of GDP. Data from Federal Statistical Office.

[7]There are minimum contributions for different age brackets that are at least matched by employers. Contribution rates range from 7 percent at 25 years of age to around 18 percent before retirement. Employers can be more generous in selecting higher employer matches or by offering plans covering a larger share of the salary than the legal minimum.

[8]Pension funds have to guarantee a minimum interest rate on capital. In 2020, this is 1 percent. The legal minimum benefits are guaranteed by a national reinsurance mechanism in case of a fund insolvency. Moreover, there is the risk of conversion rate decreases for example due to increasing life expectancy of the insured individuals.

[9]The individuals' choice between an annuity and a lump at retirement in Switzerland has been studied by Bütler and Teppa (2007).

limited voluntary contributions of up to 6'826 CHF per year (year 2019).[10]

The buy-in option Within the second pillar, insureds have the possibility to make additional voluntary contributions additionally to their mandatory payments. They can choose to contribute up to their personal so-called *buy-in potential.* The buy-in potential is a function of the individual's contribution history and her current income level (see eq.1)

$$TFP_{it} = \sum_{s=25}^{t} \psi_s y_{it} - w_{it}^p \tag{1}$$

where y_{it} refers to labor income at age t, ϕ_s to the contribution rate at a given age, and w_{it}^p to the pension wealth at age t. Thus, the term $\sum_{s=25}^{t} \psi_s y_{it}$ refers to the hypothetical mandatory retirement savings obtained with current salary at age t since the age of 25. Specifically, the buy-in potential is the difference between the hypothetical retirement savings that the individual would have accumulated through mandatory contributions if she had earned the current salary since the age of 25, and the actual accumulated occupational pension wealth. It arises, for instance, from transitions to higher paying jobs, employment breaks or unemployment spells. Consider for example a 50 years old individual with constant income of 100'000 CHF since the age of 25. A wage increase by 10 percent translates to a potential for voluntary contributions to her pension fund of 21'500 CHF.[11] Overall, individuals in Switzerland transferred in 2017 5.6 billion CHF via the buy-in option to their pension funds.

Fiscal incentives for voluntary retirement contributions The institutional setting offers several fiscal benefits for individuals making voluntary contributions to their occupational pension plans:[12] (i) contributions are deductible in full from household's income, allowing to reduce both the average and the marginal income tax rate due to the progressive income tax scheme; (ii) accumulated pension wealth is excluded from the wealth tax base. (iii) returns from retirement accounts are tax-exempt. In Appendix A, we show that the net tax savings range between around 10 percent (at the bottom of the income distribution) and 40 percent (at the top of the income distribution) of the contributed amount, with substantial heterogeneity across different administrative areas (cantons) which have large autonomy in

[10]Brown and Graf (2013) have shown that individuals' contributions to this form of private retirement saving account are positively associated with their level of financial literacy.

[11]If the income declines again to the original level of 100'000 CHF or below, the buy-in potential would become zero again.

[12]Similar fiscal benefits apply to voluntary contributions to private retirement accounts. Notice that additional contributions to the occupational pension plans provide additional coverage for survivors and in case of disability. Individuals in Switzerland are subject to both income and wealth taxation. Taxation is levied by the federal government, cantons and municipalities. Tax rates differ between cantons and municipalities (see Figure A1)

setting tax rules.[13] The accumulated pension wealth is subject to taxation when paid out. Annuities are taxed as income while a special tax applies to lump-sum withdrawals.[14]

1.2 Pension funds background

We collaborated with a Swiss company that manages two occupational pension funds insuring, in the year 2017, 6'100 employees from around 500 firms. The funds insure employees from small and medium size companies from all sectors. The assets managed by the two funds amounted to 1.081 billion CHF at the end of 2017. Contribution rates, matching formula, and conversion rates are typical for pension funds in Switzerland.[15]

1.3 Administrative pension fund data

We use administrative data at the individual level for the years 2013 to 2019 provided directly by the two pension funds. Data include error-free information on annual labor income, mandatory contributions and end-of-year stock of pension wealth, buy-in potential, information on projected pension wealth and retirement benefits under the current contribution scenario. The data also include information on transactions (voluntary contributions in the form of buy-ins). Further, the administrative records include information on individuals' gender, marital status, municipality of residence, age, and tenure in the firm. Finally, the data is linked with the registration status of individuals in the pension app in June 2019.

1.3.1 Sample characteristics

The sample consists of individuals working for a firm covered by one of the two pension funds. Insureds drop out of the sample when they retire or change job and the new employer ensures workers with a different pension fund. We restrict the sample to individuals between 25 and 65 years of age with annual earnings between 45'000 CHF (corresponding to a typical minimum wage for a full time worker) and 250'000 CHF (corresponding to the 99-percentile of the income distribution in Switzerland).[16] Moreover, because the institutional setting does

[13]Credit Suisse AG estimates that the additional rate of return of a buy-in compared to a stock market investment for a wealthy 50 year old couple amounts to 18.04 percent (Credit Suisse AG. 2020. "Freiwillige Vorsorge: In die 2. Säule oder in die Säule 3a einzahlen?". accessed Nov 10, 2020. `https://www.credit-suisse.com/ch/de/articles/private-banking/freiwillige-vorsorge-2-oder-3-saeule-201712.html`

[14]The special tax on lump-sum withdrawals is calculated regardless of the personal income and wealth situation(Lichtensteiger and Schubiger, 2019)

[15]Fund A had a conversion rate of 5.8 percent and fund B of 5.9 percent in the year 2017. The median conversion rate in Switzerland was 6 percent in 2017 (Swisscanto Vorsorge AG. 2020. "Schweizer Pensionskassenstudie 2017". accessed Nov 5, 2020. `https://www.swisscanto.com/media/pub/1_vorsorgen/pub-107-pks-2017-ergebnisse-deu.pdf`). The funds coverage ratio was above 100 percent (110 percent and 104 percent) in 2017

[16]Although there exists no national minimum wage in Switzerland, several cantons and cities have introduced minimum wages for full time workers ranging from approximately 40'000 CHF (Ticino) to 48'000

not allow individuals with zero buy-in potential to increase contributions, these are dropped when we empirically investigate the role of the pension app on contribution behavior. In the final sample are 16940 observations from 3552 distinct individuals. In 2016, insureds in our sample are on average 42.75 years old, with around 61 percent of men and a median labor income of 88'006 CHF. The sample is fairly representative of the national population of workers with respect to gender, age and labor income.[17]

1.3.2 Key facts

To understand the potential role of digitalization in retirement planning behavior, we first document key facts in the administrative data about:[18] (i) the degree of retirement preparedness of older workers; (ii) the extent of the potential for voluntary contributions; (iii) voluntary contribution decisions.

Heterogeneity in replacement rates from occupational pensions To what extent do occupational pensions replace labor income before retirement? Answering this question may help gain insights into the importance of voluntary contributions for retirement preparedness and interventions that aim at promoting them.

We leverage the administrative data and consider the ratio between projected pension annuity and current labor income as a measure of the replacement rate from occupational pensions for insureds older than 60 years.[19] On average, insureds are expected to receive around 23.2 percent of their current income as retirement benefits from their pension fund.[20] Importantly, the data show a large heterogeneity in the projected second pillar replacement rate for a given income level (see Figure D1). This heterogeneity reflects different earning histories and voluntary contribution decisions, and highlights the importance of additional voluntary contributions for the retirement preparedness of (at least some) individuals. The

CHF (Geneva). The upper percentile of the overall income distribution is retrieved from the Swiss Earnings Structure Survey of the Federal Office of Statistics (2020).

[17]Table H1 reports a comparison of key statistics in our sample and in the Swiss labor force for the year 2016. Around 61 percent of insureds in the two pension funds are male compared to around 59 percent in the Swiss labor force. Insureds in the sample are on average 42.75 years old compared to 41.8 in Switzerland and the median annual wage is slightly higher in the sample (CHF 88'006) compared to the Swiss labor force (CHF 78'024).

[18]To document these facts, we restrict the sample to the period 2013-2016, before the introduction of the pension app.

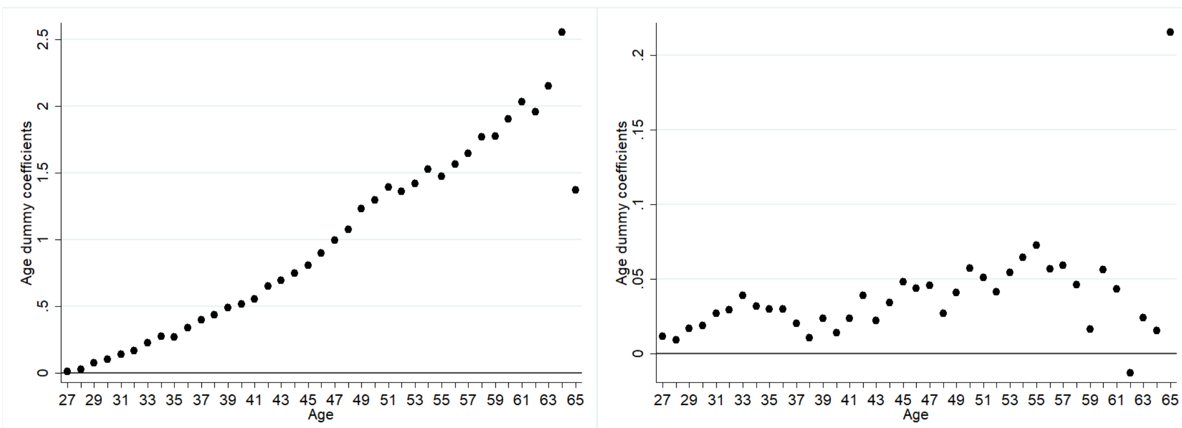
[19]The projected pension benefits are based on an individual's current pension wealth and assuming constant mandatory contributions until retirement. This projection is communicated to the insureds in the annual letter and the pension app. It resembles the replacement rate from the second pillar at retirement, often used as an indicator for the adequacy of pension benefits. Our measure is just a proxy for the actual replacement rate at retirement for individuals aged below 65.

[20]The occupational pension benefits are complemented by the benefits from the first pillar. For the median income earner the replacement rate from the first pillar is around 24 percent (data from Federal Statistical Office).

results of multivariate regression analysis, reported in appendix D, show that male workers, higher income earners, and a longer tenure in a firm are associated with higher levels of projected replacement rates.

Heterogeneity in potential for tax-favoured voluntary contributions Do insureds have the possibility to make tax-favoured contributions and increase their replacement rate at retirement? The buy-in potential provides a measure of the magnitude of voluntary contributions individuals could choose to allocate additionally to their retirement account, and of the extent of fiscal benefits individuals are entitled to.

The accumulated buy-in potential is substantial and increasing with individual's age: close to retirement, individuals are entitled to buy-in (and thereby deduct from their personal income tax) almost twice their annual labor income on average (see Figure D2).[21] There is large heterogeneity in buy-in potential to income ratio for a given age. The dispersion in this ratio also increases with individuals' age.[22]



(a) Potential buy-in to income ratio (b) Probability to make a voluntary contribution

Figure 1: Estimated age-profiles

Notes: The graphs plot the coefficients of the age dummies of the regression model in eq. (9). Dependent variable on the left panel is the ratio of the potential buy-in amount to the occupational pension fund over individuals' labour income. Dependent variable on the right panel is a dummy indicating whether an individual is making a voluntary contribution to her pension fund in a given year. Data from two Swiss pension funds for the years 2013 to 2016.

In Appendix D, using multivariate regressions we show the buy-in potential to income ratio decreases, as expected, with employee's tenure with the current employer, while we

[21] Figure D3 depicts the average income profile over individual's age.

[22] The standard deviation of potential buy-in to income ratio increases from around 0.20 between ages 25 and 35 to 1.65 between ages 55 and 65. 9.5 percent insureds show no potential of buy-in which can reflect either voluntary decisions of contributions or declining wage profiles (e.g., through a series of negative permanent income shocks) over the working life.

do not find evidence of a gender gap nor a direct association with income. Because also high-income earners are predicted to have substantial buy-in potential to income ratios (see also Figure D5), liquidity or borrowing constraints do not seem a likely explanation for the limited take-up of fiscal benefits. The estimated age profile of buy-in potential to income ratio (in Figure 1.a) confirms an increasing age pattern over the working life, and the possibility for individuals to make contributions corresponding to twice their labor income when they approach retirement age.[23]

Determinants of voluntary contributions Who is taking advantage of the tax incentives for retirement savings?

Overall, 2.81 percent of the insureds use the buy-in option to increase their pension wealth each year prior to the introduction of the pension app. The share of insureds who make use of the buy-in option at least once before retirement is substantial. About 70 percent of insureds make at least one buy-in by their normal retirement age (see Figure D7). Buy-ins represent substantial investments for insureds: the contributed amounts correspond to around 33 percent of the individuals' annual labor income. Voluntary contribution behavior is characterised by a hump-shape age profile over the insureds' working life (see Figure D4), resembling well-known age patterns in stock market participation (see, e.g., Fagereng et al. 2017 for Norway and Daminato and Pistaferri 2020 for the US). The estimated age-profile for the probability to make a voluntary contribution (see Appendix D for details on the estimation strategy), is depicted in Figure 1.b. The contribution rate increases from around 1.5 percent among insureds younger than 40 years of age to peak at around 7 percent when individuals are aged 60. Interestingly, nearly 20 percent of individuals make a buy-in right before retiring, at the age of 65.

The ratio of the contributed amount to income also increases with age. While individuals younger than 50 years of age contribute on average around 19 percent of their annual income when they decide to do so, individuals above the age of 50 make voluntary contributions of 43 percent of their annual income (see Figure D8). Further, we find the share of individuals choosing to make a buy-in increases with labor income (see Figure D4 and Table D1) and that women are more likely to make voluntary contributions.

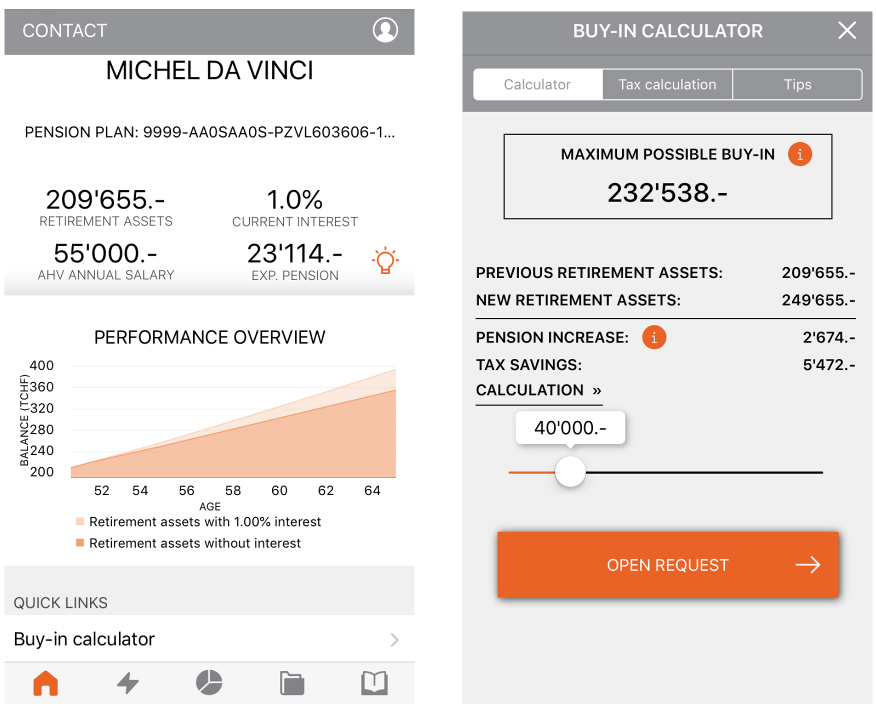
2 The digital pension application

To facilitate individual retirement planning and the process of making voluntary contributions, the company managing the two funds developed a new digital pension application. Before describing the application, it is useful to characterise the baseline communication

[23] To separate age, cohort and year effects, we follow Deaton and Paxson (1994) and impose the parametric restriction that time effects sum to zero once we include a time trend (see Appendix D for details).

strategy and the steps needed to make a voluntary contribution to the retirement plan in its absence.

Baseline communication and application strategies The two pension funds have communication and contribution application strategies which are typical among occupational pension funds in Switzerland. Each year, all insureds receive a letter with information on their occupational pension plan. The letter includes information on the current retirement account balance, the projected expected retirement wealth and pension benefits under the current mandatory contribution plan and minimum interest rate, as well ass the individual's buy-in potential. Each time an individual wishes to exercise the voluntary buy-in option, she is required to write a letter to the pension fund with the request. The pension fund will later send a buy-in offer and an invoice.



(a) Home screen (b) The buy-in calculator

Figure 2: The pension app

Notes: The figures show screenshots of the pension app. Panel (a) depicts the home screen of the pension app and panel (b) presents the buy-in calculator. The link to the buy-in calculator is visible on the bottom of the home screen. Source: Pension app of the pension funds.

Content of the pension app Panels (a) and (b) of Figure 2 report screenshots of the home screen of the pension app and its buy-in calculator, respectively. On the one hand, the pension app provides the same information that is already sent annually to all insureds through the letter at the insured's home address: information about the current account balance, the current minimum interest rate, projected expected retirement wealth and pension benefits given constant contributions, as well as the individual buy-in potential (see panel (a)). On the other, the app also allows to obtain an estimate of the tax savings from making a buy-in contribution and it simplifies the process of making these contributions. As shown in panel (b), the user can obtain an estimate of the tax savings (in CHF) from contributing a desired monetary amount by moving a slider.[24] Further, the app allows to directly apply for making a buy-in contribution of the selected amount with a simple "click" on the "open request" button.

Usage of the pension app Although the pension app does not track individual user behavior, we can observe aggregate statistics on navigation behavior.[25] The buy-in calculator is the most frequently used tool within the app, with the tool accessed 66 percent of the times an insured logs in (see also Figure A2). 3.4 percent of the times a user logs in the app, a buy-in request is made directly through the pension app.

2.1 Conceptual framework

To formalize the possible role digitalization can play in the contribution behavior to tax-favoured retirement saving plans, we consider optimal voluntary contribution decisions in a stylized life-cycle setting. In this simple model, detailed in Appendix B, individuals choose the amount of wealth to invest in the second pillar in each period they work, to maximise their expected lifetime utility. They do so in the presence of two frictions: (i) misperception about the tax savings from contributions and (ii) transaction costs for making a buy-in. These frictions are motivated by the institutional setting. On the one hand, the optimal voluntary contribution decision requires individuals in Switzerland to compute the tax savings they can obtain from these contributions. This in turn requires individuals to be aware about the presence of the tax incentives (Bhargava and Manoli, 2015) and to know their marginal income tax rates.[26] On the other, the application process is complex and requires a substantial amount of time, as described in Section 2. These "hassle" costs capture then the opportunity cost of time required to understand and then go through the process of submitting an application.

[24] The baseline estimates for tax implications are based on the administrative data of the pension fund. The insured has the possibility to adapt the data underlying the calculations. For example, a married individual could add the income of the partner in order to obtain more precise tax estimates.

[25] We use data for iOS devices from April 2018 - April 2019.

[26] Misperception about tax savings is then related to limited knowledge, which can result from costly information acquisition (Caplin and Dean, 2015) and can therefore be optimal (as in Lusardi and Mitchell 2014).

In Appendix B, we show that the simple model predicts both reducing transaction costs and individuals' misperception about tax benefits from contributions increases the probability to make a buy-in. Therefore, because the pension app is designed to provide digital information about the tax benefits from contributions and to simplify the process of making a buy-in, we hypothesise that providing individuals with access to the pension app will induce an increase in contributions. Importantly, the model highlights that, without additional information, it is not possible to disentangle between competing behavioral mechanisms (increase in knowledge about the tax benefits vs. reduction in the "hassle" costs from making a contribution) by simply observing a contribution response to the introduction of the app. We describe how we explore whether the pension app affects contribution behavior mainly through reducing misperception about tax savings or transaction costs in the next section.

2.2 Methods

We take two complementary approaches to study the role of the digital pension app on individuals' contribution behavior to their occupational pension plans. First, we estimate the intent-to-treat (ITT) effect of introducing the app adopting a quasi-experimental design that exploits its staggered roll-out across two distinct pension funds, managed by the same company, over time.

Second, we conduct a field experiment, randomizing reminder invitation letters among non-uptakers of the pension app. The experimental setting allows us to: (i) estimate the local average treatment effect (LATE) of using the pension app on contribution behavior, using treatment assignment as an instrument for app registration status; (ii) provide evidence on the main mechanism underlying the contribution response to the pension app usage, exploiting different nudges towards the content of the digital pension app (simplified application process vs. calculation of tax savings from contributions).

In the next section we discuss the identification strategy we use to identify the effect of introducing the digital pension application and present the ITT estimates. The experimental results are reported in section 4.

3 Quasi-experimental evidence from the pension app roll-out

3.1 The natural experiment

The company managing the two pension funds (fund A and fund B) decided to adopt a staggered roll-out of the pension app across the two funds over time. Insureds with fund A had access to the pension app before the end of the fiscal year 2017, in contrast to those insured with fund B. The timeline of the natural experiment is depicted in Figure 3. The differential timing of the introduction of the pension app across the two funds was decided by the company's management solely based on administrative considerations.

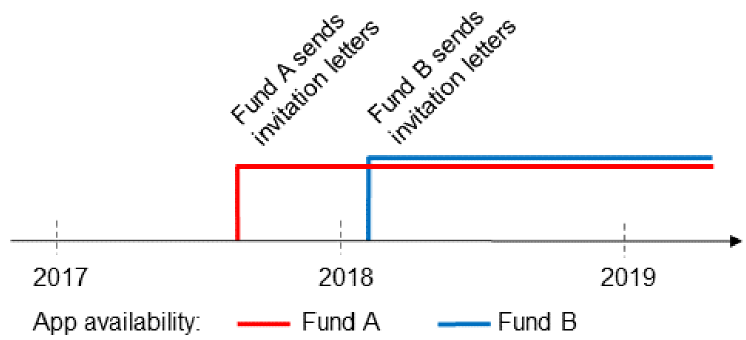


Figure 3: Timeline of introduction of the pension application

Notes: The figure shows schematically the timeline of the introduction of the pension app and the timing of sending the invitation letters. Source: Authors.

The two pension funds invited their insureds to access the pension app through a letter sent by regular mail at the insured's residence. The letter informed the insured a new pension app was available.[27] The letter included a personalized activation code and a description how to download, install and activate the app. The fund offered a little gift in form of a swimming bag to the first 100 insureds who registered. Specifically, fund A sent out letters inviting insureds to register to the pension app by post on August 31, 2017 (iOS) and again on November 27, 2017 (iOS & Android). Individuals insured with fund B received the letter later on February 16, 2018 (iOS & Android). All individuals received a reminder to access the app together with their annual pension statement in February 2019. In the pre-intervention period, the overwhelming majority of voluntary contribution decisions were taken by insured individuals in the months of November and December.[28] After having received the invitation letter, insureds could choose to download the pension application and register using the personalized log-in code included in the invitation letter. In June 2019, we observe who had registered to the pension app until that date.

3.2 Identification strategy

The first goal of this paper is to estimate the causal effect of providing individuals with the possibility to use the pension app (through the delivery of the invitation letter) on voluntary contributions to their occupational pension plans. The ideal setting for estimating this policy-relevant parameter would be one in which access to the pension application (and thus delivery of the invitation letters) had been randomly assigned to part of the insureds within the two

[27] A copy of the letters sent by the two funds is included in Appendix A.

[28] As shown in Figure D10, 70 percent of all voluntary buy-ins are made in December, 14 percent in November and 5 percent in October. All the earlier months have shares below 3 percent .

funds, with no information spillover to insureds that did not receive it. One could then simply compare the voluntary contribution choices of the two groups. In our setting, all insureds received the invitation letter and hence the possibility to access the pension app, but with different timing depending on their occupational pension fund.

Our identification strategy exploits the staggered roll-out of the pension app across the two pension funds over time. We adopt an event study design, where the "event" is defined as an insured individual receiving the invitation letter to register in the pension app in a given year, exploiting the fact that individuals insured with the two funds obtained access to the pension app in different fiscal years. Hence, the control group for an individual that received the invitation to access the pension app in 2017 consists of individuals receiving the same invitation in 2018. To control for aggregate shocks that may affect contribution behavior, we condition on year fixed effects. Further, because the event occurred at the pension fund level, in a given period, we condition on pension fund fixed effects to capture unobserved time-invariant fund-specific factors potentially driving the differential timing in the delivery of the invitation letters.

The main identifying assumption is that receiving the invitation letter in a given year is exogenous to the individual voluntary contribution to the retirement saving account, conditional on a set of determinants we control for. We believe this is a reasonable assumption to take in this context because the timing decision was entirely based on administrative considerations made by the management of the two funds and could not be manipulated by the individual insured. To lend credibility to the validity of this empirical strategy, we first show that the two funds insure individuals with similar characteristics and pre-treatment contribution behavior. Table E1 reports a comparison of selected individual characteristics by fund for the year prior to the introduction of the pension app in the first fund. Insureds are balanced with respect to age, wage, tenure with the current employer, accumulated pension wealth across funds. Importantly for our goal of estimating the ITT effect of introducing the digital app on voluntary contributions, individuals insured with the two funds have statistically equal buy-in potential and contribution behavior (both voluntary contribution rates and contributed amounts) prior to the introduction of the pension app. Although there is a higher share of men among insured with fund B, the F-test rejects the joint significance of all observable characteristics. Second, we conduct standard placebo and pre-treatment parallel trend tests to show that contribution behavior does not respond before the invitation letter is received. Importantly for the validity of our identification strategy, the two pension funds insure individuals from several hundred small and medium sized companies, ruling out any effects being driven by company-specific dynamics.

Further, we need to assume there is no interaction between individuals receiving and not receiving the invitation letter to access the pension app (i.e., the SUTVA condition is satisfied). Since every insured working in a given company received the invitation letter at the same time, a violation of this assumption in our setting would require information spill-over (e.g., discussing about the fiscal benefits from voluntary retirement contributions) to occur between employees of a company insured with fund A and those of a different company insured with fund B. We argue this is quite unlikely considering the relatively small size of the two pension funds.

Since the event study design also exploits the variation from the introduction of the pension app to insureds with fund B in 2018, an additional assumption we are taking is that the treatment effect does not vary over time Goodman-Bacon (2021). To relax the latter assumption, we also estimate the ITT effect of providing individuals with the possibility to use the pension app adopting a canonical difference in differences (DiD) strategy. We keep observation periods prior to 2018 (when fund B introduces the pension app for its insureds), and use individuals in fund B (who "never" receive the invitation letter) as a control group for the behavior of individuals insured with fund A.[29]

Interpretation This research design allows to identify the short-term (1-year) intent-to-treat (ITT) effect of providing access to the pension app. Although we observe who eventually chooses to register into the pension app, the identification of the average effect of the pension app on voluntary contribution decisions is difficult in this setting because individuals are self-selecting into registering in the pension app. This selection process is likely to be driven by unobservable individual-specific factors. Because the invitation letters were sent to all individuals insured with a pension fund at the same time, we cannot identify the effect of using the pension app exploiting this natural experiment.[30] In Section 4, we describe the experimental design we adopt to obtain a credible source of exogenous variation in app usage. This will allow us to obtain an estimate of its causal effect on retirement contribution behavior and evidence on the main mechanism underlying the behavioral response.

3.3 Empirical specification

To quantitatively estimate the effect of providing access to the pension app on individuals' voluntary contributions, our identification strategy leads us to the following event-study specification:

$$y_{ift} = \alpha + \sum_{e=-4}^{2} \beta_e APT_{f(t+e)} + \gamma X_{ift} + \delta_f + \theta_t + \epsilon_{ift} \tag{2}$$

[29]The standard common trend assumption is still required in this setting: the evolution of contribution choices over time (between years 2016 and 2017) of individuals insured with fund A would have been the same, absent the introduction of the pension app, as that of individuals insured with fund B.

[30]One could think of exploiting the variation in the timing in the introduction of the pension app (and then the delivery of the invitation letters) as an instrument for the registration in the pension app, under the assumption that receiving the invitation letter affects contribution choices only through the usage of the pension app. However, we do not find significant relation between the probability to be registered in the pension app in June 2019, and the timing of the pension app introduction (see Table C1.)

where y_{ift} is an indicator for the outcome of interest of individual i, insured with pension fund f in year t, $APT_{f(t+e)}$ ($e = -4, -3, ..0$, with -1 the omitted category) are event-time indicators, X_{ift} is a set of individuals' characteristics, and δ_f and θ_t denote fund and year dummies, respectively. Our main indicator for contribution decisions is a dummy variable indicating whether an insured used the buy-in option to increase her accumulated occupational pension wealth in a year. Further, we estimate the model using the log of total contributed amount in a year as dependent variable. $APT_{f(t+e)}$ are dummy variables that capture the distance in years before and after insured i received the possibility to access the pension app, i.e., the dummies take value one if fund f sends the invitation letter to register in the pension app in $(t - e)$. Because we omit the dummy variable indicating the year prior to the event $APT_{f(t-1)}$, the coefficients of interest β_e ($e = -4, -3, ..0$) indicate the effects on voluntary contributions e years before or after providing access to the pension app, relative to the year before the fund sent the invitation letter. The absence of statistically significant differences in contribution choices across individuals insured with fund A and fund B before the funds sent the invitation letters to register in the app, β_e ($e = -4, -3, -2$), would support the validity of our main identifying assumption.

The set of controls include individuals' age and age squared, gender, marital status, log labor income and log number of years of tenure in the firm. Moreover, we include fund and year fixed effects. We restrict the sample for estimation to individual-time observations where insureds are eligible to make a voluntary buy-in (i.e., we exclude observations corresponding to zero buy-in potential). Further, to avoid the results are confounded by differential changes in the composition of the insureds in the two funds over time, we condition on the group of insureds at the time the pension fund introduces the app. We estimate our main event study specification from eq.(2) that exploits the variation in the roll-out of the pension app with a Probit model for the indicator of buy-in contributions and OLS for the log of buy-in contributions. Standard errors are clustered at the individual level.

As discussed in Section 3.2, we estimate the ITT effect of making the app available also adopting a canonical DiD, restricting the sample to observations prior to the introduction of the pension app in fund B. In this case, we estimate the "static" specification:

$$y_{ift} = \alpha + \beta POST_{ft} * \delta_f + \gamma X_{ift} + \delta_f + \theta_t + \epsilon_{ift} \tag{3}$$

where $POST_{ft}$ is a time of intervention dummy taking value one in the period after fund A sent the invitation letter to register in the pension app, and all other variables are as in eq.(2).

3.4 Quasi-experimental results

To gain insights about the change in individual choices around the time of pension app introduction, we start estimating eq.(2) separately for pension fund A (introducing the app in 2017) and pension fund B (introducing the app in 2018). Because this descriptive analysis only exploits changes in contribution choices over time, we set $\theta_t = 0$.

The estimation results are reported in Panels (a) and (b) of Figure E1 for fund A and fund B, respectively. They show non significant estimates for the years before the individuals received the invitation letter to register in the app β_e $(e = -4, -3, -2)$, and a jump in the probability that insureds make a voluntary contribution in the year the pension app was introduced, in both pension funds. Specifically, the contribution rate increases by around 1 and 2 percentage points among insureds in fund A and B, respectively.[31] Although there is no evidence of significant time trend in contribution rates in a given fund (β_e $(e = -4, -3, -2)$ are all statistically equal to zero), one needs to be cautious in interpreting these results as effects of introducing the app because they assume that there are no shocks occurring at the same time as the introduction of the app.

To relax this assumption and exploit the variation in the roll-out of the pension app while conditioning on time fixed effects, we estimate our main event-study specification (2). Figure 4 plots the impacts of the invitation letter to register in the app across event time.[32] As we described above, these are the probability to make a voluntary contribution at event time e, relative to the year before the introduction of the pension app, conditioning on individuals' characteristics, fund and time fixed effects. The figure also reports 90 and 95 percent confidence intervals around the estimated effects.

The figure shows that the trend in contribution rates of individuals insured in the two funds was parallel before the introduction of the pension app (β_e $(e = -4, -3, -2)$ are all statistically equal to zero), supporting the validity of the identifying common trend assumption. In the year when the insureds receive the invitation letter to register in the pension app, $e = 0$, the results show a jump in the probability to make a voluntary contribution. We find a similar event time pattern when we estimate eq.(2) for the log of total contributed amount (see Table E3 and Figure E3).

To quantitatively assess the magnitude of this effect, we also estimate the difference in differences specification (3) on the full estimation sample as well as on the restricted sample before the year 2018.[33] The results show substantial ITT effects of providing access the the

[31] Overall, this evidence is confirmed when we use the log total contributed amount as dependent variable, as shown in Figure E2 in Appendix E.

[32] The full estimation results of the Probit and linear probability models for the probability to make a voluntary contribution are reported in Columns 1 and 2, respectively, of Table E3 in Appendix E.

[33] The "static" specification of the event study design corresponds to the difference in differences specification (3). While the 'static" specification of the event study design uses the entire sample period for estimation, the difference in differences specification only uses data prior to year 2018, and fund B as a control group.

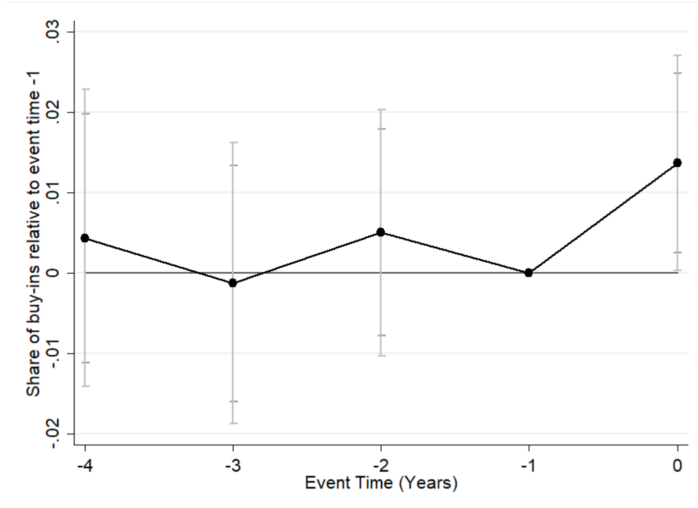


Figure 4: ITT: Event study coefficients for the probability to do a buy-in

Notes: The graph reports marginal effects of the event study coefficients from a Probit model based on the model in eq. (2). Dependent variable: buy-in dummy indicating a positive yearly contribution (buy-in) to the occupational pension fund. The event is receiving the invitation letter to for the first time. Event dummies are reported relative to year prior to event. The error bars show 90 and 95 percent confidence intervals for cluster robust standard errors at the individual level. All estimates are reported in Table E3. Data from two Swiss pension funds from 2013-2018.

pension app. As reported in Table 1, we find that making the pension app available to the insureds increases the overall probability to make a voluntary contribution by around 1.8 percentage points. The estimation of the DiD model yields similar results.[34]

This is an economically large effect considering the average contribution rate of 2.82 percent in the pre-treatment period. Providing access to the pension app therefore increases the share of individuals who are making an additional voluntary contribution to their retirement account by around 65 percent . Further, we find that the contributed amount increases by around 13.73 percent following the introduction of the pension app. Our point estimates for the effect of introducing the digital pension application on contribution behavior are substantially larger than those of other interventions previously analysed in the literature.[35]

[34]As shown in Table E2, we obtain estimates of very similar magnitude estimating both ES and DiD specifications using a linear probability model. As a robustness check, we conduct an analysis with a placebo treatment of fund A in the years 2016. Results are reported in Table E7 and show no effects in the year prior to the actual introduction of the pension app.

[35]Dolls et al. (2018) estimate that, in response to a letter sent via regular mail including retirement benefits projections, individuals increase contributions to private retirement accounts by 6 percent on average, in Germany. Goda et al. (2014) find that sending retirement income projections together with enrollment information increases the average contribution level to employer retirement accounts by 3.6 percent average in the US. In comparison, our estimate for the increase in total contributions after having the possibility to access the pension app is twice and four times larger, respectively.

Table 1: Static event study (ES) & DiD specifications for ITT effect

	Buy-in indicator		**Log contributed amount**	
	ES	DiD	ES	DiD
	(1)	(2)	(3)	(4)
	Probit	Probit	OLS	OLS
Post*Fund	0.0180**	0.0155*	0.1373**	0.1243*
	(0.0085)	(0.0088)	(0.0641)	(0.0702)
Year FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Mean outcome in t - 1	0.0281	0.0298	0.2788	0.2949
Observations	15355	11279	15478	11364

Notes: Difference in differences estimates based on eq. 3. The table reports marginal effects from a Probit model in Column (1) and (2), and OLS estimates in Columns (3) and (4). Specifications (1) and (3) are estimated with the entire sample whereas specifications (2) and (4) are estimated with the restricted sample before the year 2018. Dependent variable in (1) and (2): buy-in dummy indicating a positive yearly contribution (buy-in) to the occupational pension fund. Dependent variable in (3) and (4): log amount of voluntary contributions to the occupational pension fund. Estimates are conditional on fund, year, gender, and marital status fixed effects. Moreover, all specifications control for second order polynomial of age, for log wage and for log tenure. Standard errors in parentheses are robust and clustered on the individual level. Data from two Swiss pension funds covering the years 2013–2019. The event defining the post dummy is receiving the invitation letter to register in the pension app for the first time.

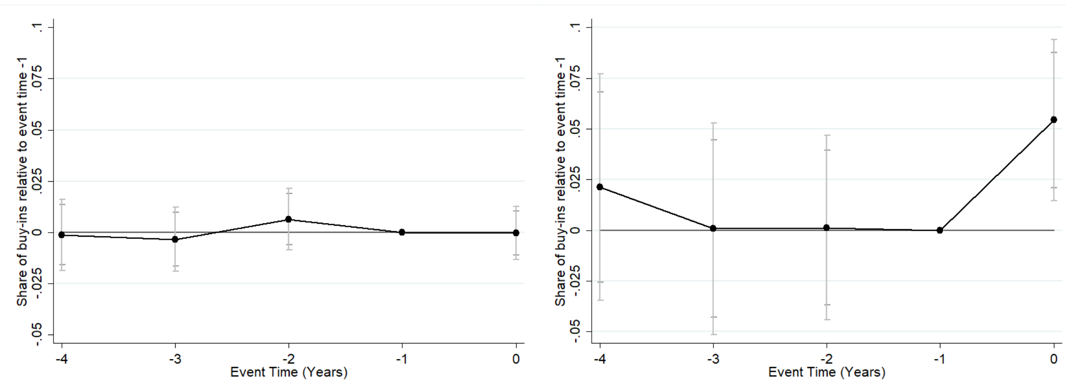
3.4.1 Heterogeneity in contribution response

The event study estimates presented above are not informative about whether the behavioral response to the introduction of the app is driven by the actual registration in the app. Further, the ITT estimates do not allow to disentangle between the importance of the app in reducing transaction or tax benefits-related information acquisition costs. To make some progress, we start by exploring treatment effect heterogeneity, before reporting on the experimental results.

Invitation letter or registration to the pension app? First, we explore treatment effect heterogeneity based on the pension app registration status. To do this, we use pension app registration data observed in June 2019.[36] Overall, 1'206 individuals from fund A (20.5 percent) and 503 individuals from fund B (19.7 percent) registered in the pension application by mid 2019. We run our event study regression model (2) separately for individuals who eventually registered in the digital app and for those who never registered. Therefore, we use individuals self-selecting into registering in the pension app after receiving the invitation letter in 2018 as a “control group” for the behavior of insureds self-selecting into using the pension app after receiving the invitation letter in 2017. Although this strategy compares

[36] As discussed in Section 1, we observe who had registered to the pension app in June 2019 for the first time.

the behavior of "similar" (e.g., more sophisticated) individuals, we wish to stress that it does not allow to recover a causal estimate for the effect of the pension app. Besides the registration decision being clearly endogenous, an additional caveat is that we cannot rule out that individuals receiving the letter in 2017 signed up to the pension app after the end of the fiscal year.[37] Nonetheless, this analysis provides some suggestive evidence about whether app usage is the main mechanism underlying the behavioral response in this setting.



(a) only never registered individuals

(b) only registered individuals

Figure 5: Event study coefficients by registration status (buy-in indicator)

Notes: The graph reports marginal effects of the event study coefficients from a Probit model based on the model in eq. (2). Panel (a) shows the estimates for the restricted sample with individuals that never registered in then pension app and panel (b) shows the estimates for the restricted sample with only individuals that have registered in the pension app by mid 2019. Dependent variable: buy-in dummy indicating a positive yearly contribution (buy-in) to the occupational pension fund. The event is receiving the invitation letter to for the first time. Event dummies are reported relative to year prior to event. The error bars show 90 and 95 percent confidence intervals for cluster robust standard errors at the individual level. All estimates are reported in Table E4. Data from two Swiss pension funds from 2013-2018.

On the left panel of Figure 5, we report the event study estimates for the sample of insureds who never registered in the pension app. Results show no impact of the invitation letter on the probability of making a voluntary contribution, before or after the pension funds introduced the digital application.[38] In contrast, we find a large jump in the probability to make a voluntary contribution to the occupational pension plan in the year in which the pension app is introduced among insureds that do register in the pension app (see the right panel of Figure 5). The introduction of the pension app increases the probability to buy-in in this group of insureds by around 5.4 percentage points. Given the circumstance that the

[37]In this case, the event study estimate obtained using the sample of registered individuals would understate the effect of the pension app.

[38]The complete estimation results of the event study regression models conditional on pension app registration status, for both the probability to make a voluntary contribution and the log of contributed amount, are reported in Table E4.

contribution rate among insureds that eventually register in the pension app is around 6 percent before its introduction, the estimated response is economically large. The estimation results of for the log of total contributed amount are reported in Figure E6, and confirm a behavioral response to the introduction of the pension app only among insureds that register to the pension app. This group increases the contributed amount by 47 percent after receiving the invitation letter.

Who is accessing the digital pension app? Given the observed difference in the behavioral response to the introduction of the pension app, we characterize the group of registered insureds who is demanding the digital pension-related information. On average, insureds that registered to the pension app are one year older (46.1 years old) than individuals that never registered (45.5 years old).[39] Another key fact emerging from the registration data is that higher income earners are more likely to register in the application, as shown in panel (b) of Figure D11.[40] To better characterise who chooses to access the pension app, we regress a dummy variable that takes value one for insureds who registered in the pension app, and zero otherwise, on the individual characteristics available in the administrative data (see Column 6 of Table D1). The analysis confirms that higher income is associated with a higher probability to register in the pension app. Further, men are around 9.4 percent more likely to register. Finally, longer tenure in a firm also positively correlates with the probability to register in the app.

Who is responding more to the introduction of the digital pension app? In Appendix E, we show that the contribution response to the introduction of the pension app is larger among men, higher-income earners and those individuals who have greater buy-in potential.[41] Together, these results provide compelling, though merely suggestive, evidence that the average ITT effect on contribution behavior is driven by those individuals who eventually register in the pension app. Further, they show that the group of individuals responding to the introduction of the app are those who have, ex-ante, more to gain from making a voluntary buy-in and accessing the associated tax benefits.

4 Experimental evidence

Leveraging the quasi-experimental variation in the introduction of the pension app, we can only identify the effect of making the pension app available to insureds. We administer a randomized controlled trial with non-uptakers of the pension app to gain additional insights

[39]Panel (a) of Figure D11 shows registration rate is somewhat increasing with individual age.
[40]Figure D9 reports additionally the income distribution conditional on app registration status.
[41]We do not find significant heterogeneity in the ITT effect with respect to age.

along two dimensions: (i) the effect of app usage on contribution behavior for the groups of individuals with lower willingness to adopt the digital pension app and lower contribution rates; (ii) the main behavioral mechanisms underlying the contribution response.

4.1 Experimental design and intervention

In autumn 2020, we conducted a randomized controlled trial among app non-uptakers, i.e., insureds who had yet to register in the pension app. We pre-registered the experiment at the AEA RCT registry (AEARCTR-0006590). The simple experimental design is sketched in Figure F1. We randomly assigned the 3890 insureds in our sample who were not registered in the app in October 2020 to four groups: a control group who did not receive any further reminder to register in the pension app and three treatment groups who received one of three different reminder letters.[42]

The three versions of the reminder letters are reported in Appendix F. Version I of the reminder contains baseline information about the content of the pension app, without any mention to the tax saving calculator or the feature facilitating the process of making contributions. Version II adds, to the information in version I, a nudge towards the tax savings from contributions. Specifically, we add the text "*Or do you know that voluntary savings contributions (buy-ins) can be fully deducted from income tax? Find out how big your buy-in potential is and how much taxes you could save through voluntary contributions*". A picture showing the tax savings calculator tool of the app is also reported in the letter, highlighting (in red) the estimated tax savings from a hypothetical contributed amount. Version III includes, in addition to the content of version I, an additional nudge towards the lower "hassle" costs from making a contribution using the app. The additional text in this version of the letter reads: "*In addition, the - name of the app - considerably simplifies the process of making voluntary contributions. See for yourself how easy it is to submit an application with the insured app.*". The additional picture in this letter version also shows the buy-in calculator, as in version II, but with two important differences: (i) it hides the tax saving calculator; (ii) it highlights (in red) the "open request" button.

4.2 Sample characteristics

In Table 2 we show treatment (pooled) and control groups are balanced with respect to observables in the data. G2 reports the balance on observables for each treatment group. All

[42]The pension funds sent the reminders to the individuals in their preferred language (German, French, Italian or English) via regular mail, all at the same time in November 2020. Based on our power calculations, the minimum detectable effect size for the probability of being registered in the application is a change of 4 percentage points with a 95 percent confidence level. This corresponds to a change of 15 percent compared to the pre-treatment level. The minimum detectable effect for the probability of making a voluntary contribution is a change of 1.5 percentage points with a 95 percent confidence level. This corresponds to a change of 50 percent compared to the pre-treatment level.

groups are balanced with respect to age, gender, income, pension wealth, buy-in potential, tenure in the firm and share of non-married individuals.

Table 2: Balance of observables between treatment and control groups

	Control Mean	Treatment Mean	Diff	t-test p-value
Age	43.28	43.68	-0.40	0.315
Gender (male)	0.656	0.654	0.002	0.921
Wage (CHF)	78'192	77'782	410	0.687
Pension wealth (CHF)	94'008	96'782	-2694	0.560
Buy-in potential	84'021	87'211	-3190	0.404
Tenure (years)	6.88	6.89	-0.01	0.963
Single	0.462	0.481	-0.019	0.310
Observations	974	2916		3890

Notes: The table presents means, differences and their standard errors and p-values of a t-test comparing the group means for a selection of observables in our sample. This table compares the control group which did not receive a reminder to all individuals that have received a reminder in 2020.

Using the administrative data, we observe contribution choices at the end of the years 2020 and 2021 for all insureds who have not left the pension funds at that time. There are two potential sources of attrition: (i) individuals who retire; (ii) individuals who change their employer. Overall, 223 individuals (5.7 percent) drop out of the sample by the end of year 2020 and 608 insureds (15.6 percent) drop out of the sample after receiving the reminder letter by December 2021. However, we find no differential attrition between control and the treatment groups (see results of the attrition analysis in Table G1).

4.3 Experimental results

The main goal of our experiment is twofold: (i) provide a credible source of variation for identifying the causal effect of using the pension app on contribution behavior; (ii) explore the main behavioral mechanism underlying the contribution response to the introduction of the app, exploiting the different nudges included in the letters. We start by analysing whether sending a reminder letter affected registration status and overall contribution behavior.

4.3.1 Intent-to-treat effect of sending reminder registration letters

We have shown above that observables are balanced among insureds assigned to treatment and control groups and that there is no differential attrition across the different treatments and the control groups. Therefore, since the treatment was unconfounded, we can simply compare differences in contribution behavior of treatment and control groups, and interpret these differences as intent-to-treat effects of being assigned to that group (receiving - or not - one of the three invitation letters). We further need to assume that there are no information spillovers between insureds assigned to different groups within a given firm. A violation of this assumption would imply an underestimation of the ITT of sending the reminder letters. To estimate the ITT of receiving the reminder letter, we then use the random variation from the treatment allocation at the individual level. We estimate the simple regression model:

$$y_{it} = \beta D_i + \delta X_i + \psi_t + \epsilon_{it} \tag{4}$$

where y_{it} is a registration or contribution indicator for individual i at time $t = [2020, 2021]$, D_i is the treatment indicator and θ_t is a year fixed effect. We further include a set of individual's characteristics X_i to increase the precision of the estimates. β captures then the ITT effect of sending the reminder letter. We adopt two specifications to estimate: (i) the overall effect of receiving one of the letters (D_i takes value one if an individual received any of the invitation letters); (ii) the effect of each version of the reminder letter.

The results are reported in Table 3). First, we find that receiving any reminder letter increases the share of registered individuals by around 7 percentage points (see results in Column (1)). Considering the limited adoption of the digital application in this group of insureds, with a registration rate in the control group of 7.3 percent, our results show that a simple reminder letter is very effective in increasing adoption. Interestingly, we find homogeneous registration responses across the different versions of the reminder letter (see Column 2 of Table G3). These results then indicate that neither highlighting the possibility to calculate tax savings from contribution, nor stressing the simplified application process for making voluntary contributions within the app further motivates insureds to register. This evidence complements previous findings by Bauer et al. (2022) showing that information about peers' behavior does not affect adoption of digital pension environments. However, the different version of the letter may motivate different insureds to register, with implications for their contribution response.

Although our main goal is to exploit our intervention to provide an estimate for the effect of using the digital application on contribution behavior, we also consider the ITT effect on contributions of sending a simple reminder registration letter. As shown in Columns (2) and (4) of Table 3), while we find a positive point estimate for the effect on both the probability to make a voluntary contribution (0.2 pp) and overall contributed amount (1.78 percent), the estimates are noisy and the effect not statistically significant.

4.3.2 LATE of the digital pension app

To identify the LATE of the digital pension app on contribution behavior, we instrument registration status with the random treatment assignment. Instrument exogeneity is guaranteed due to the random assignment of insureds to different treatment arms and control groups. We have provided above evidence on the strength of the instrument and that treatment assignment was in fact unconfounded. The LATE estimates need to be interpreted, as usual, as the effect on compliers, i.e., those individuals who registered to the app because they received the reminder letter. We then estimate the following equation using two-stages least squares:

$$y_{it} = \gamma APP_{i,t} + \delta X_i + \psi_t + \eta_{i,t} \tag{5}$$

where $APP_{i,t}$ is a dummy for app registration status of insured i in t and all other variables are as in eq.(4). As a first stage regression, we use 4 with the app registration indicator as outcome variable.[43] γ indicates the effect of using the app for those who register after receiving the reminder invitation letter.

Table 3: Intention to treat and local average treatment effect

	App registration	**Buy-in indicator**		**Log contributions**	
	ITT	ITT	LATE	ITT	LATE
	(1)	(2)	(3)	(4)	(5)
Treatment	0.0684***	0.0020		0.0178	
(grouped)	(0.0077)	(0.0039)		(0.0389)	
App registration			0.1365**		1.3853**
			(0.0662)		(0.6696)
Year FE	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes
p-value F test			0.0000		0.0000
Mean control	0.073	0.0130	0.0130	log(547.8)	log(547.8)
Observations	6956	6956	6956	6956	6956

Notes: Estimated marginal effect of the treatment indicator from a linear probability model are reported. Dependent variable in Columns (1) and (2) is a binary indicator for insureds that made a buy-in to their pension fund in 2020 post treatment or the year 2021 respectively. Dependent variable in Columns (3) and (4) is the log amount of buy-ins in the same period. Columns (1) and (3) present the intention-to-treat specifications and Columns (2) and (4) the estimates of the local average treatment effect from a 2SLS-IV model. All specifications control for insureds' gender, age, age squared, log income, marital status, fund membership and tenure in the firm. Clustered standard errors on the individual level are reported in parentheses. Data from two Swiss pension funds.

Instrumenting registration status with the random treatment assignment, we find a large LATE of the digital pension application on contribution behavior. The digital application increases the probability to make a voluntary buy-in by about 13.6 percentage points and the overall contributed amount by about 138.5 percent, respectively, as reported in Columns (3) and (5) of Table 3. The latter corresponds to an increase in overall annual contributions to the occupational retirement account of about 750 CHF. These causal effects are there-

[43] Since both the instrument (receiving an invitation letter) and the endogenous variable (registration to the pension app) are binary indicators, we implement a three-step approach Angrist and Pischke (2008): (i) estimate a Probit model with the dependent variable app registration status on the treatment indicator and the set of control variables; (ii) take the predicted values from this model; (iii) use these predictions as instruments for the estimation of eq.(5).

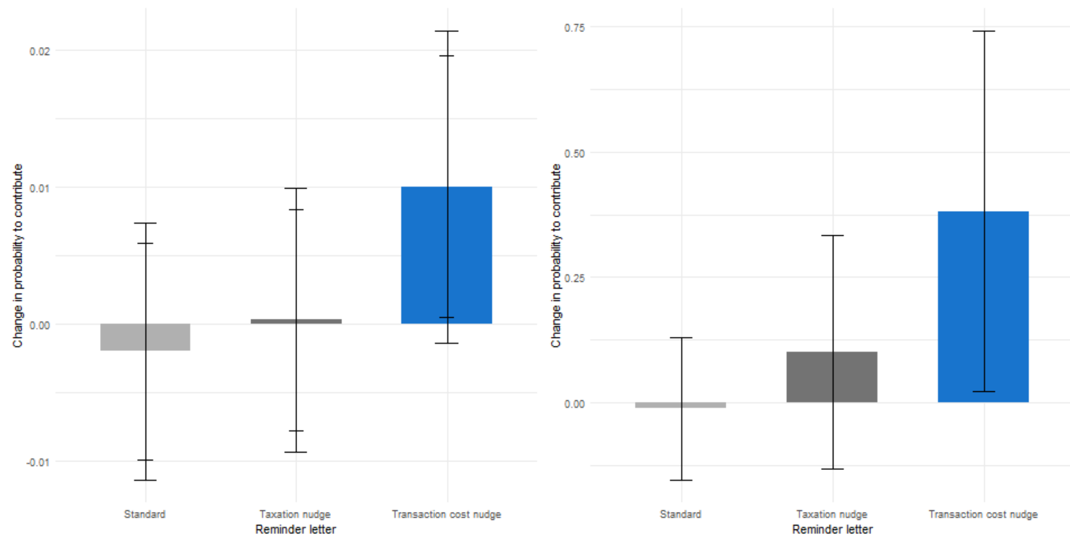
fore economically substantial and larger (though not statistically) than the merely suggestive evidence on the effect of introducing the digital application among those who eventually registered, presented in section 3.4.1. We wish to stress that these experimental results represent local estimates of the effect of the digital application for the group of individuals who registered in the app following our reminder registration letter. Although this group of insureds cannot be considered as representative of the general population, they are particularly interesting to study for understanding what motivates adoption of digital pension environments and the barriers to the take-up of financial incentives for retirement contributions.

4.3.3 Mechanisms: nudge towards tax savings vs. lower "hassle" costs

How is the digital pension application affecting contribution behavior to the tax-favoured retirement accounts? To provide some evidence on the mechanisms underlying the contribution response to the introduction of the app, we leverage the different nudges in the reminder registration letters. We first test whether imperfect knowledge about tax savings or transaction costs, or both, play a role in individuals' contribution behavior to retirement saving accounts, regardless of registration status. To do this, we simply exploit the random treatment assignment to obtain an estimate of the ITT effect of sending a reminder letter nudging towards the digital application providing information about tax savings or simplifying the process of making a voluntary buy-in. We then estimate eq.(4) separately for each reminder registration letter. The results of the ITT analysis by letter, reported in panel (a) of Figures 6 and G1 are striking:[44] while sending the baseline letter or the letter nudging towards the tax savings from contributions has no effect on neither the probability to make a voluntary buy-in nor the overall contributed amount, the nudge towards the lower "hassle" costs of making a contribution using the digital application has a relevant effect on contribution behavior. Merely receiving the "lower transaction costs from using the app" letter increases the probability of making a buy-in by about 1 percentage points, and the overall contributed amount by around 10 percent (significant at the 10 percent level). On the one hand, these results suggest that the feature of the pension application facilitating the process of making a voluntary contribution is more important than the computation of the tax savings from contributions. On the other hand, it provides additional evidence in support of the hypothesis that it is really the access to the digital application (through the simplified application process from making a contribution) driving the contribution response to its roll-out.

In the previous section we have provided an estimate for the LATE of accessing the digital application for the group of compliers registering after having received any of the reminder letters. Exploiting the different nudges within letters, we can estimate the effect of the pension app on contribution behavior for different groups of compliers, i.e., insureds registering in

[44]The full estimation results are reported in Table G4.



(a) ITT effect of reminder letters

(b) LATE of the digital pension app

Figure 6: Mechanisms: tax savings or lower "hassle" costs

Notes: The graph in panel (a) plots the estimates of the ITT effect of sending reminder letters on the probability to make a contribution. Each bar corresponds to the effect of receiving a specific reminder letter (baseline, tax savings, transaction costs). The graph in panel (b) plots the estimates of the LATE of using the pension app on the probability to contribute, obtained using the random treatment assignment as instrument for registration status. Each bar represents the LATE for the subgroup of insureds receiving one of the letter types. 90 percent and 95 percent confidence intervals are reported.

the digital application after receiving the baseline letter vs. the nudge towards tax saving vs. lower "hassle" costs. Because the different instruments potentially induce different groups of insureds to register in the digital application (more interested in the tax savings vs. simplified application process features), we interpret potential LATE heterogeneity across these groups as additional evidence on the relative importance of channels underlying the contribution response to app usage. We estimate eq.(5) using the treatment assignment of app registration status, separately for each treatment group. The estimation results are reported in panel (b) of Figures 6 and G1. Consistently with the treatment effect heterogeneity by letter type presented above, we find no effect of using the pension app among those individuals who received the baseline letter or the letter nudging towards the digital application computing the tax savings from making a contribution. The results show that, among those individuals registering in the app after receiving the nudge towards lower "hassle" costs, using the digital pension application increases the probability to make a buy-in by around 38 percentage points, and the contributed amount by about 400 percent (significant at the 5 percent level). These results show that the overall LATE of the digital application on contribution behavior (estimated in the previous section) is driven by those individuals receiving a nudge towards the digital application simplifying the process of making a contribution. They further point towards transaction costs as an important barrier to the take-up of financial incentives for retirement contributions.

5 Conclusion

This paper has presented quasi-experimental and experimental evidence on the effects of providing access to a digital pension application on actual retirement contribution behavior.

We show that the introduction of the digital pension application induced a substantial retirement contribution response in a setting where individuals are already annually informed about future expected pension benefits. This is important in that previous studies on the role of information in retirement saving decisions mainly focused on limited knowledge about expected pension benefits (Mastrobuoni, 2011; Goda et al., 2014; Dolls et al., 2018). Finding that providing access to the digital pension app increases retirement contributions remains policy relevant, irrespective of the understanding of the underlying mechanisms.[45] This is especially important in light of the circumstance several government agencies and pension funds around the world have introduced or are planning to roll-out similar digital tools to help individuals save for retirement. Moreover, our results point towards the "hassle" costs from making a contribution as an important barrier to retirement contributions. They show that the reduction in these transaction costs is the most important mechanism underlying the contribution response to the introduction of the digital pension application. These results are relevant for the ongoing process of digitalization in the retirement sector, as they inform the design of future digital pension environments about the importance of simplifying the process of making a transaction. They also inform models of savings and portfolio choice, highlighting the importance of including transaction or fixed participation costs (Kaplan and Violante, 2014; Fagereng et al., 2017; Choukhmane, 2019).

This study shows that, once a pension app is developed and linked to retirement account data, a low-cost, scalable, intervention consisting in sending an invitation letter to register in the app has the potential to have important effects on economic well-being. While the welfare implications of untargeted nudges to make additional contributions such as "you are not saving enough for retirement'' may be ambiguous because, clearly, not everyone is not saving enough for retirement, access to the digital application allows individuals to simply observe "raw" information about the pension situation and reduce the "hassle" costs they need to pay to make a contribution. The larger retirement contribution response that we find among higher-income earners and individuals with larger potential for tax-favoured contributions, that is, workers having, ex-ante, more to gain from making an additional contribution to the

[45]On the relevance of the policy effect in the absence of the identification of the underlying mechanisms see, e.g., Chetty (2015).

retirement saving account, also points to the intervention being welfare-improving. Future research should, however, explore whether the higher retirement contributions reflect into higher overall retirement savings. This evidence could be used to conduct a sound welfare analysis. Further, while understanding what drives the retirement contribution response of low savers is important (as in Beshears et al. 2015), more work is needed to explore which barriers to the take-up of financial incentives for retirement savings are important for others groups.

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Appendix - For Online Publication

A Institutional setting and informational intervention

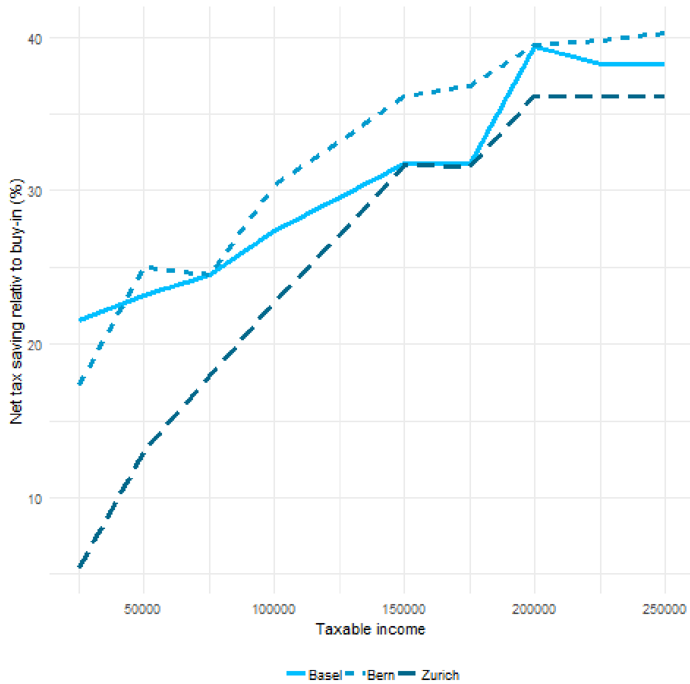


Figure A1: Illustration of tax benefits from a voluntary buy-in

Notes: The graph depicts estimates of tax benefits from a 10'000 CHF buy-in for different income levels in Basel, Bern & Zurich. Numbers are retrieved from the online tax calculator of the Swiss federal government. For each city, we report the estimated tax-benefits for an single, protestant individual in the year 2019. Tax benefits for a 10'000 CHF buy-in are computed as the difference between instantaneous savings of the the income tax and the tax on the equivalent lump-sum payout at retirement. The calculations assume that the individual receives 10'000 CHF back as lump-sum payment at retirement, and abstract from returns on pension wealth and benefits from preferential wealth and interest taxation in the pension fund. Tax benefits are then computed as the difference between the income tax savings today and the tax on the equivalent lump-sum payout at retirement. Local administrative areas in Switzerland (cantons) have large autonomy in setting tax rules. The numbers are in line with those reported in (OECD, 2018) where the estimated present value of taxes saved through contributions to a retirement savings plan in Switzerland is around 26 percent of the present value of contributions for an average earner, and up to 47 percent for high income individuals.

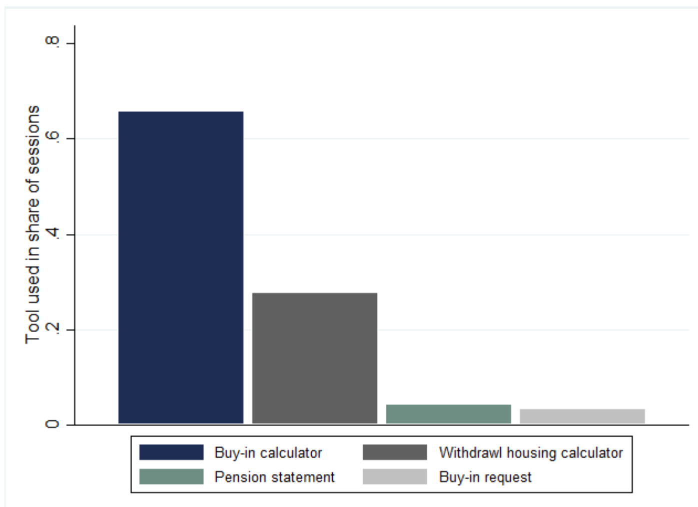


Figure A2: Usage of pension app

Notes: The graph depicts the share of user sessions in which an individual used a specific tool in the pension app. The graph shows exemplary how individuals used the pension app. It refers to data for iOS devices for a one year period from April 2018 to April 2019. Data for fund A.

Persönlich / Vertraulich
450.0013
[redacted]

Datum: 31. August 2017
Referenz: [redacted]

Kontakt: [redacted]
Tel. direkt: [redacted]
E-Mail: [redacted]

Neue App für die Versicherten der [redacted] und neue Website

Liebe Versicherte

Die [redacted] freut sich ausserordentlich, Ihnen wie in den vergangenen Monaten angekündigt nachfolgend den **Aktivierungscode** für Ihre Registrierung in der neuen [redacted]-App zustellen zu dürfen.

u1029

Aktuell steht die App auf dem iPhone- und iPad zur Verfügung.

Ende Oktober werden wir die App auch auf dem Android-Betriebssystem zur Verfügung stellen.

Ein extra entwickeltes Video gibt Ihnen einen Einblick über Inhalt und Nutzung der neuen App. Sie finden das Video auf der ebenfalls neu aufgebauten [redacted]-Website unter [redacted] oder direkt auf der Einstiegsseite der App.

[redacted]

Um Ihre App in Betrieb zu nehmen, gehen Sie folgendermassen vor:

- Geben auf Ihrem iPhone oder iPad im Browser (z.B. „Safari“) [redacted] ein. Sie werden direkt zur [redacted]-App im AppStore weitergeleitet. Natürlich können Sie die App auch direkt im AppStore suchen.
- Installieren Sie die Applikation, indem Sie auf "Laden" klicken und öffnen Sie diese.
- Bei der Erstregistration müssen Sie zur Sicherheit die gefragten Informationen eingeben, inkl. Ihren Aktivierungscode in diesem Schreiben.
- Bei jedem weiteren Öffnen der Applikation können Sie direkt über "Login" einsteigen.

ACHTUNG: die ersten 100 Versicherten, die sich registrieren erhalten einen coolen „[redacted]-Fisch“, um damit einen kühle Fluss runter zu treiben oder auch im nächst gelegenen See eine Abkühlung zu geniessen!

Sollten Sie Fragen haben zur Nutzung der App oder sollten technische Störungen auftreten, dann wenden Sie sich bitte per Mail oder Telefon an [redacted]

Wir freuen uns auf viele begeisterte Rückmeldungen! Bitte nutzen Sie dazu auf dem iPad im Menu „Übersicht“ der App oder auf dem iPhone unter „Kontakt“ oben links die Feedback-Funktion. Ihre Rückmeldung wird dann direkt dem [redacted]-Support zugestellt.

Freundliche Grüsse

[redacted]

[redacted]

Allgemeine Hinweise

1. Mit der App haben Sie direkten Zugriff auf das [redacted]-Archiv. Die [redacted] betreibt seit 2014 ein digitales Archiv. Die historischen Dokumente wurden nicht nachträglich gescannt.
2. Mit der App können Sie die Entwicklung Ihres Sparkontos bei der [redacted] einsehen. Die [redacted] hat den heutigen Kontenplan seit 2009 im Einsatz. Sie können Ihre Daten also bis maximal 2009 zurückverfolgen.

[redacted]

Figure A3: Invitation letter

B A simple model

To derive hypotheses on the role of the pension app on voluntary contribution behavior, we introduce a simple model in which an insured decides whether and how much to contribute voluntarily to her pension fund over her working life. This stylized framework builds on the model of DellaVigna (2018). Compared to that model, where the individual starts to save and keeps on contributing every period to her pension fund, we consider the choice of making one-time buy-ins. Further, we include tax incentives explicitly.

In each period t, the individual derive utility from consumption c_t and are assumed to maximise expected lifetime (T periods) utility choosing how much to contribute to their occupational pension plan B_t:

$$\max_B E_t \sum_{s=0}^{T-t} \beta^s u(c_{t+s})$$

where $\beta < 1$ is the per-period discount factor. In each period t, she earns after-tax labor income $(1-\tau)y_t$, and capital income from her financial wealth with a gross rate of return R_f. If she chooses to make a voluntary buy-in of an amount B, she transfers B CHF of resource available for consumption into the tax-favoured retirement saving account. This allows her to obtain tax savings equal to τB in taxes in the current period t. The contributed amount will earn a gross interest R_f, assumed to be fixed and known all the way until retirement, in $N-t$ periods. At the age of retirement N, she then receives a lump-sum amount equal to the after-tax (τ_N) defined contribution wealth accumulated in the retirement account w_N^p. We assume that $\tau_0 < \tau_T$, which describes the typical tax schedule in Switzerland.

The dynamic budget constraint can therefore be written as:

$$a_t = R_f a_{t-1} + (1-\tau)y_t - c_t - (1-\tau)B_t + w_t^p(1-\tau_R)\mathbb{1}(t=N) \tag{6}$$

where a_t is beginning-of-period financial wealth and $B_t = w_t^p - R_f w_{t-1}^p$. We consider the case in which, to contribute an amount B, the individual has to reduce her consumption in period t, which yields marginal utility $u'(c_t)$. In this simple setting, the net utility gains Z_t from contributing an amount B in period t are then given by:[46]

$$Z_t = -(1-\tau)B_t u^{'}(c_t) + (\beta R_f)^{(N-t)}(1-\tau_N)B_t u^{'}(c_N)$$

Consider now the case in which making a buy-in comes at an immediate effort or transaction cost k. Further, we allow individuals to have imperfect knowledge of the tax benefits from making a contribution. Specifically, individuals' degree of misperception about the tax

[46] If the individual instead simply transfers resources from her checking account into her retirement saving account, the net utility gains are given by $Z_t = (\beta R_f)^{(N-t)}(\tau - \tau_N)B_t u^{'}(c_R)$, with $Z_t > 0$ provided we have $\tau > \tau_N$.

savings from making a contribution is captured by the coefficient $\theta \in (0,1)$. In this case, eq.(6) becomes:

$$a_t = R_f a_{t-1} + (1-\tau)y_t - c_t - (1-\theta\tau)B_t + B_t(1-\theta\tau_N)\mathbb{1}(t=N)k\mathbb{1}(B_t>0)$$

and the net utility gains Z_t from contributing an amount B in period t are given by:

$$Z_t = -\underbrace{\Big(k + (1-\theta\tau)B_t u^{'}(c_t)\Big)}_{\text{Perceived net costs}} + \underbrace{(\beta R_f)^{(N-t)}(1-\theta\tau_N)B_t u^{'}(c_N)}_{\text{Perceived discounted net benefits}} \tag{7}$$

To simplify the calculations, we assume a constant marginal utility of consumption that is normalized to 1, and a discount rate that equals the inverse of the interest rate, $\beta = (R_f)^{-1}$. Eq.(7) becomes:

$$Z_t = -k + \theta B(\tau_t - \tau_N)$$

The decision rule to make a contribution is $Z_t > 0$.[47]

Therefore, we have $\frac{\partial Pr(Z_t>0)}{\partial k} < 0$ and $\frac{\partial Pr(Z_t>0)}{\partial \theta} > 0$, that is the probability to make a buy-in in period t decreases with transaction costs and increases with the individual knowledge about the tax savings from making a contribution.

Observing an increase in the probability individuals make a contribution following the introduction of the digital pension app, would support the hypothesis that digitalization reduces he "hassle costs" of contributions and/or reduces the degree of misperception about the tax savings from these contributions.

[47] Conditional of a positive net gain from a buy-in ($Z_t > 0$), the individual could consider to postpone the buy-in to the next period. An individual contributes in period t if $Z_t > 0$ and $Z_t > Z_{t+1}$. The condition for not postponing a contribution associated with a net gain in utility is then:

$$B\theta(\tau_t - \tau_{t+1}) > k(1-\beta)$$

C Feasibility of IV approach

A possible IV approach may exploit the difference in the timing of the introduction of the pension app. This identification strategy would use the fund of an individual as an instrument for being a registered user of the pension app in 2019. Table C1 presents the first stage for such an IV approach where we estimate whether the fund membership can predict the registration status of individuals in 2019 (when we observe the registration status). The first stage results for *fund* are not sufficiently powerful in order to pursue an IV identification strategy.

Table C1: First stage of possible IV approach

	Registration status indicator	
	(1)	(2)
	Probit	LPM
Fund indicator	-0.0277	-0.0284
	(0.0268)	(0.0280)
Controls	Yes	Yes
Observations	1871	1873

Notes: First stage of a possible IV. The table reports marginal effects from a Probit model in Column (1), and OLS estimates in Column (2). Dependent variable in (1) and (2): registration status dummy indicating whether an individual was registered in the pension app by June 2019. Independent variables are a fund dummy, a gender dummy, and marital status fixed effects. Moreover, both specifications control for second order polynomial of age, for log wage and for log tenure. Standard errors in parentheses are robust and clustered on the individual level. Data from two Swiss pension funds covering for the year 2019.

D Descriptive analysis

In this Appendix, we report descriptive analysis and additional details on the estimation of the age profiles of buy-in potential to income ratio and voluntary contribution behavior.

Estimating the age profile of buy-in potential to income ratio To separate age, cohort and year effects and estimate the age-profile of buy-in potential to income ratio, we follow Deaton and Paxson (1994) and impose the parametric restriction that time effects sum to zero once we include a time trend. We specify the buy-in potential to income ratio of individual i, aged a, belonging to cohort c, in year t, as:

$$\frac{TFP_{i,a,c,t}}{y_{i,a,c,t}} = \alpha + \beta_a \delta_a + \beta_c \psi_c + \beta_t \theta_t + \beta_0 t + \gamma X_{i,a,c,t} + \epsilon_{i,a,c,t} \tag{8}$$

where $TFP_{i,a,c,t}$ is the potential for tax-favoured voluntary contributions, $y_{i,a,c,t}$ is income, δ_a ψ_c and θ_t are dummies for age, cohort and year, t is a time trend, $X_{i,a,c,t}$ is a set of covariates (gender, log income, tenure in the firm, marital status) and $\epsilon_{i,a,c,t}$ an error term. We impose the restriction $\sum \beta_t = 0$ to eq.(8).

Estimating the age profile of voluntary contribution decisions We specify the discrete choice of contribution to the occupational pension plan by individual i, aged a, belonging to cohort c, in year t, as:

$$pr\left(P_{i,a,c,t} \mid z\right) = pr(\beta_a \delta_a + \beta_c \psi_c + \beta_t \theta_t + \beta_0 t + \gamma X_{i,a,c,t} + \epsilon_{i,a,c,t} > 0) \tag{9}$$

where $P_{i,a,c,t}$ is a dummy variable indicating whether the individual makes a positive voluntary contribution to the occupational pension plan and all other variables are as in eq.(8). We again impose the restriction $\sum \beta_t = 0$ to eq.(9). Alternatively, we parameterize age effects including a second-order polynomial in individual's age and setting $\sum \beta_a = 0$ and $\beta_0 = 0$ in eq.(9). We estimate eq.(9) using a probit and a linear probability model.

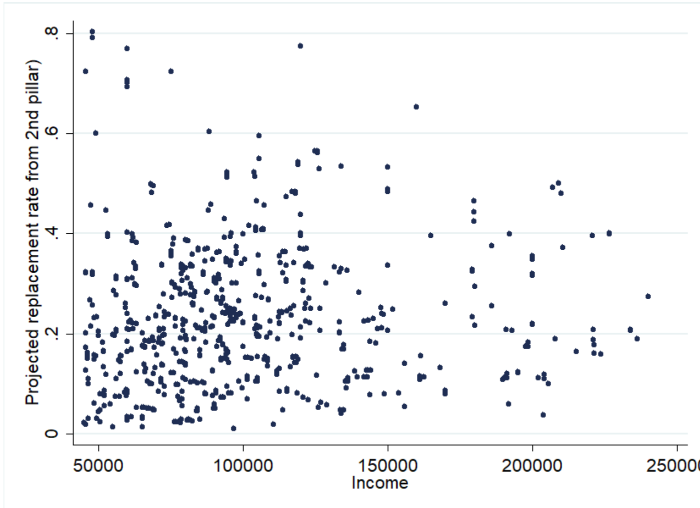


Figure D1: Projected replacement rate from second pillar
Notes: The graph shows the projected replacement rate from the occupational pension fund. The projected replacement rate is calculated as the ratio of the projected annuity over the current income. The graph depicts only observations for individuals above the age of 60. The graph excludes outliers with replacement rates above 1. Data from two Swiss pension funds.

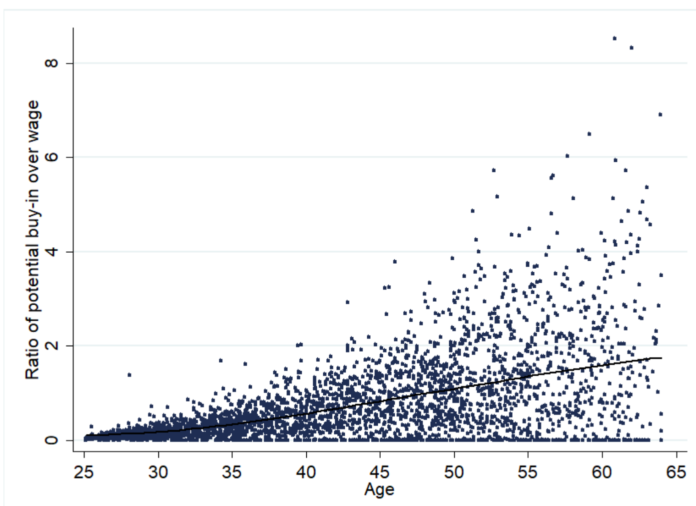


Figure D2: Potential buy-in to income ratio over age
Notes: The graph plots the scatter plot and local polynomial smoothing (black line) of the ratio of potential buy-in to wage over insureds' age for the pre-treatment year 2016. Data from two Swiss pension funds.

Table D1: Determinants of projected replacement rate, potential buy-in, voluntary contributions and pension app registration

	Projected annuity	**Potential buy-in**		**Buy-in indicator**		**App registration indicator**
	(1)	(2)	(3)	(4)	(5)	(6)
	OLS	OLS	OLS	LPM	LPM	LPM
Age	-0.0027	-0.0034		-0.0022		-0.0149
	(0.0019)	(0.0155)		(0.0020)		(0.0108)
Age (squared)	-0.0000	0.0007^{***}		0.0000^{*}		0.0001
	(0.0000)	(0.0002)		(0.0000)		(0.0001)
	0.0262^{***}	-0.0244	0.0043	0.0549^{***}	0.0564^{***}	0.2233^{***}
	(0.0063)	(0.0450)	(0.0480)	(0.0087)	(0.0090)	(0.0282)
Gender (male)	0.0102^{***}	0.0023	-0.0135	-0.0191^{***}	-0.0173^{***}	0.1022^{***}
	(0.0039)	(0.0274)	(0.0289)	(0.0060)	(0.0062)	(0.0211)
Tenure (log)	0.0197^{***}	-0.1319^{***}	-0.1231^{***}	-0.0084^{***}	-0.0088^{***}	0.0438^{**}
	(0.0020)	(0.0153)	(0.0168)	(0.0026)	(0.0029)	(0.0187)
Constant	Yes	Yes	No	Yes	No	Yes
Marital Status FE	Yes	Yes	Yes	Yes	Yes	Yes
Age FE	No	No	Yes	No	Yes	No
Cohort FE	No	No	Yes	No	Yes	No
Year FE	Yes	Yes	Constrained	Yes	Constrained	No
Time trend	No	No	Yes	No	Yes	No
Observations	9385	9385	8205	9385	8205	2057

Notes: Estimates for descriptive models and for the age-profiles based on eq. 8 and 9. The table reports OLS estimates in all Columns. For robustness checks, we report estimates from a Probit model for Columns (4)-(6) in Table D2. Dependent variable in (1): projected annuity from occupational pension plan over current income. Dependent variable in (2) and (3): ratio of potential for voluntary contributions (buy-ins) to the occupational pension fund over wage. Dependent variable in (4) and (5): buy-in dummy indicating a positive yearly contribution (buy-in) to the occupational pension fund. Dependent variable in (6): registration status dummy indicating whether an individual was registered in the pension app mid 2019. Specifications (1), (2) and (4) include as independent variables the second order polynomial of age, a gender dummy (positive if male), log wage, log tenure with the current employer as well as on year and marital status fixed effects. Specifications (3) and (5) include as independent variables age dummies, log wage, a gender dummy (positive if male), log tenure with the current employer, cohort fixed effects and a linear time trend. Specification (6) is restricted to the cross-section in 2019 and include as independent variables the second order polynomial of age, a gender dummy (positive if male), log wage, log tenure with the current employer as well marital status fixed effects. Standard errors in parentheses are robust and clustered on the individual level. Data from two Swiss pension funds covering the years 2013–2016 and 2019.

Table D2: Robustness: Determinants of potential buy-in and pension app registration

	Buy-in indicator		App registration indicator	
	(4)	(4b)	(6)	(6b)
	LPM	Probit	LPM	Probit
Age	-0.0022	0.0028	-0.0149	-0.0017
	(0.0020)	(0.0022)	(0.0108)	(0.0012)
Age (squared)	0.0000*	-0.0000	0.0001	
	(0.0000)	(0.0000)	(0.0001)	
Wage (log)	0.0549***	0.0440***	0.2233***	0.2139***
	(0.0087)	(0.0063)	(0.0282)	(0.0263)
Gender (male)	-0.0191***	-0.0163***	0.1022***	0.1047***
	(0.0060)	(0.0057)	(0.0211)	(0.0216)
Tenure (log)	-0.0084***	-0.0079***	0.0438**	0.0434**
	(0.0026)	(0.0023)	(0.0187)	(0.0186)
Constant	Yes	No	Yes	
Marital Status FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	9385	9309	2057	2054

Notes: Estimates for descriptive models corresponding to the results in Table D1. The table reports marginal effects from a Probit model in Columns (4b) and (6b), and corresponding estimates from a linear probability model (LPM) in Columns (4) and (6). Dependent variable in (4), (4b): buy-in dummy indicating a positive yearly contribution (buy-in) to the occupational pension fund. Dependent variable in (6) and (6b): registration status dummy indicating whether an individual was registered in the pension app mid 2019. Specifications (4) and (4b) include as independent variables the second order polynomial of age, a gender dummy (positive if male), log wage, log tenure with the current employer as well as on year and marital status fixed effects. Specifications (6) and (6b) is restricted to the cross-section in 2019 and include as independent variables the second order polynomial of age, a gender dummy (positive if male), log wage, log tenure with the current employer as well marital status fixed effects. Standard errors in parentheses are robust and clustered on the individual level. Data from two Swiss pension funds covering the years 2013–2019.

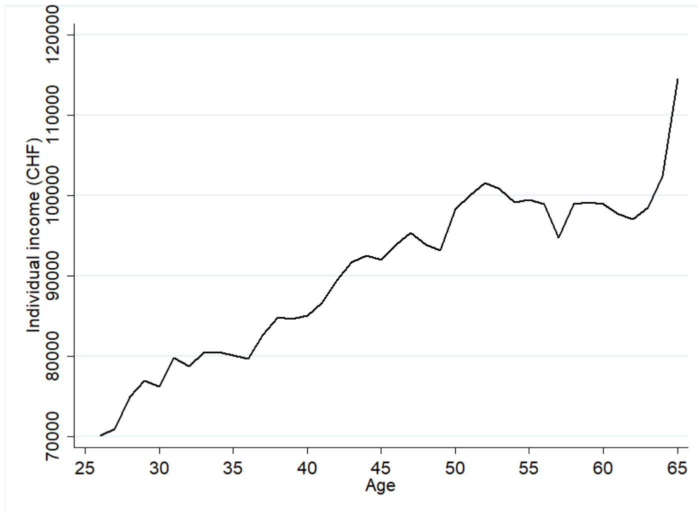
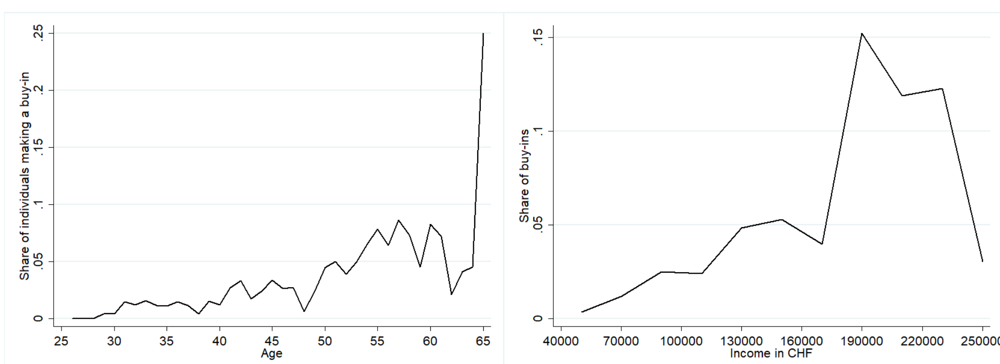


Figure D3: Income profile over age

Notes: The graph depicts the income profile of individuals over age. The graph shows the average income for each year of age. Data from two Swiss pension funds.

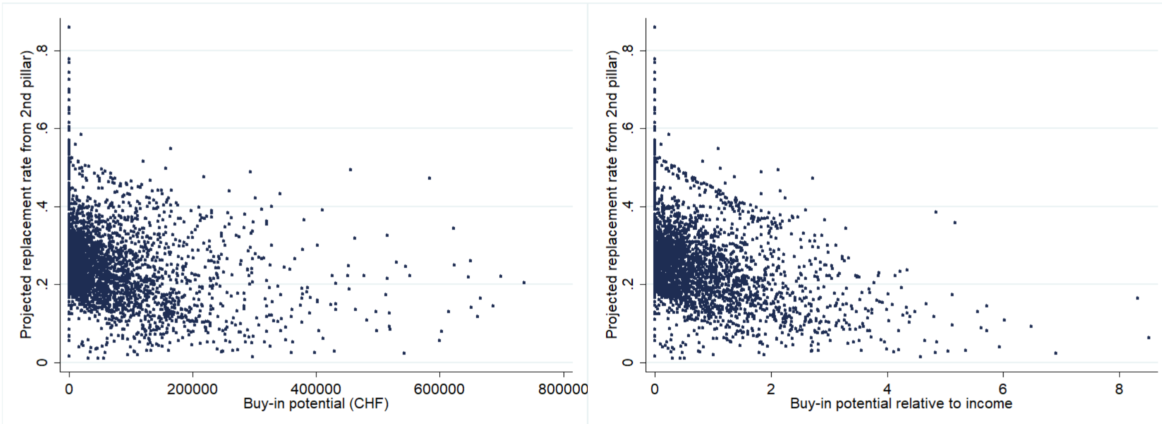


(a) By individual's age

(b) By individual's income

Figure D4: Share of insureds making a voluntary contribution

Notes: The graphs depict the share of individuals that are making a voluntary buy-in in a given year over individuals' age in panel (a) and over individuals' labour income in panel (b). Data from two Swiss pension funds for the years 2013 - 2016.



(a) Buy-in potential (b) Buy-in potential over wage

Figure D5: Projected replacement rate and buy-in potential
Notes: The graph depicts the projected replacement rate from the occupational pension fund over an individuals' buy-in potential in panel (a) and over the ratio of buy-in potential over labour income. Both graphs refer to the cross-section in the year 2016. Data from two Swiss pension funds.

Figure D6: Potential buy-in to income ratio in last year before retirement
Notes: The graph depicts the ratio of the potential buy-in over individuals' last three years average labour income. The sample is restricted to the last three years before the legal retirement age. Data from two Swiss pension funds.

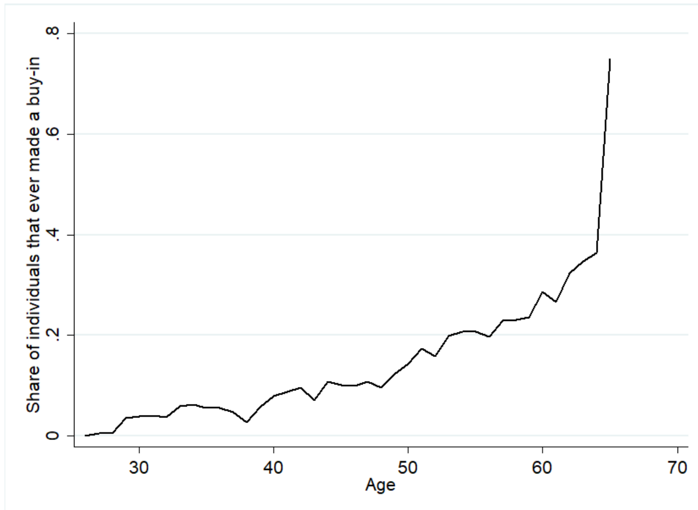
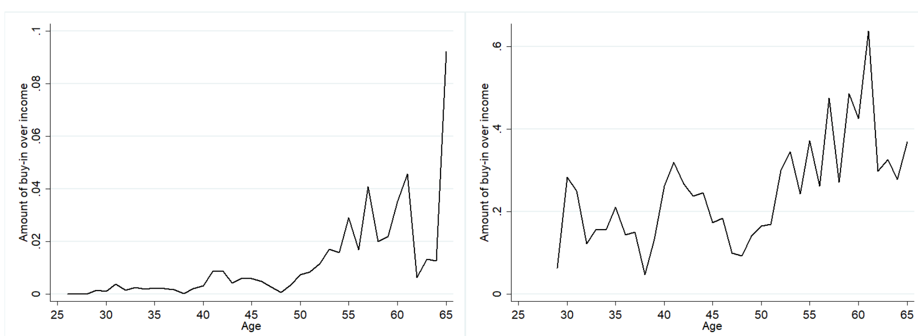


Figure D7: Share of people that has ever made a voluntary contribution by age

Notes: The graph depicts the local polynomial smoothing of the share of individuals that has ever done a voluntary contribution to her occupational pension fund. Data from two Swiss pension funds for the years 2013 - 2016.



(a) unconditional

(b) conditional on making a buy-in

Figure D8: Buy-in to income ratio over age

Notes: The graph depicts the ratio of buy-in amounts over individuals' labour income in the year of the contribution. Panel (a) considers the full sample whereas panel (b) restricts the sample to individuals that are making a buy-in. The graphs show the average ratios for each year of age. Data from two Swiss pension funds for the years 2013 - 2016.

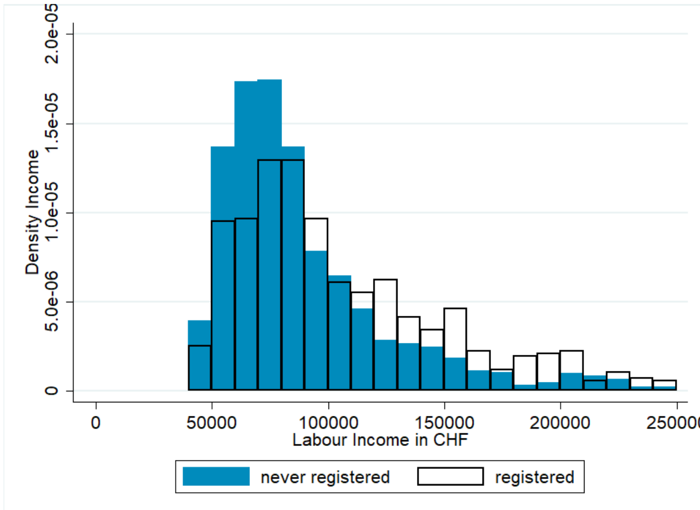


Figure D9: Histogram of income by app registration status

Notes: The graph depicts the histograms of labour income for the cross-section in the year 2019. The sample is divided into individuals who have never registered in the pension app (blue) and individuals that have registered in the pension app (black). Data from two Swiss pension funds.

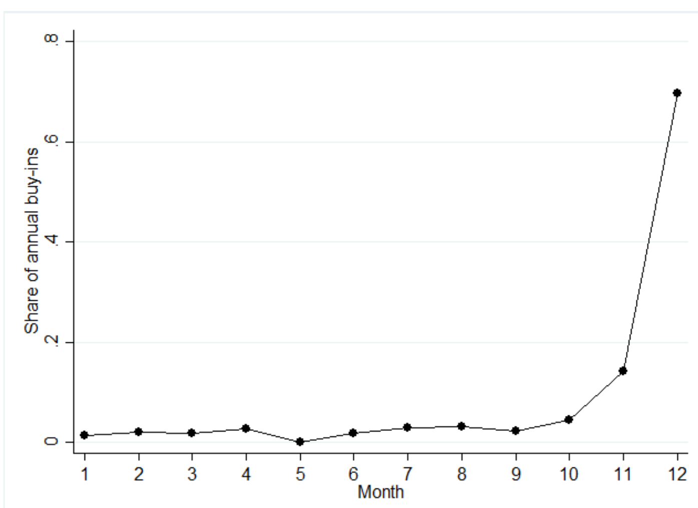
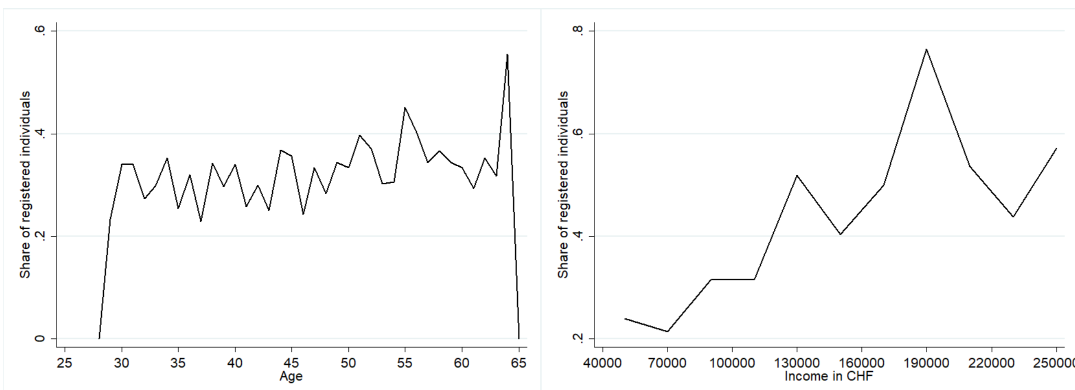


Figure D10: Timing of voluntary buy-ins.

Notes: The graph shows the share of buy-ins that occur in a specific month relative to all buy-ins. The graph depicts collapsed data for the years 2013 - 2016, hence before the introduction of the pension app. Data from two Swiss pension funds.



(a) By individual's age

(b) By individual's income

Figure D11: Registration status over age and income

Notes: The graphs depict the share of individuals that are registered in the pension app over individuals' age in panel (a) and over individuals' labour income in panel (b) for the cross-section in the year 2019. Data from two Swiss pension funds.

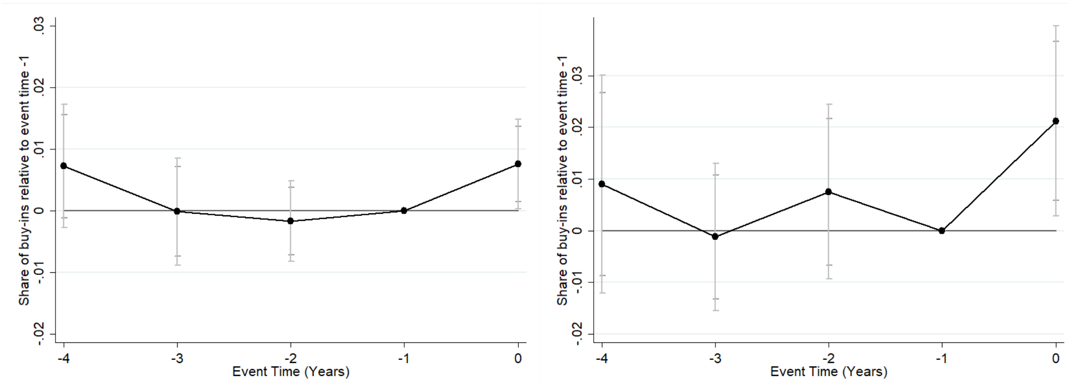
E Additional results: quasi-experimental evidence

Table E1: Summary Statistics - by fund for year 2016

	Fund A mean	**Fund B** mean	difference	**t-test** test statistics
Age	42.39	42.63	0.24	(0.43)
Gender (male)	0.58	0.79	0.21	(8.17)
Wage (log)	11.31	11.28	-0.02	(-1.06)
Tenure in firm	4.60	4.53	-0.07	(-0.26)
Projected replacement rate	0.24	0.25	0.01	(1.35)
Potential buy-in (CHF)	76022.87	74799.24	-1223.6	(-0.22)
Buy-in (binary)	0.03	0.03	-0.002	(-0.18)
Buy-in amount (log)	0.30	0.27	-0.030	(-0.34)
Observations	2631	422	3053	

Notes: Summary statistics by fund in the year 2016 for insureds age, the share of male individuals, the log wage, the tenure with the current employer in years, the projected replacement rate, the potential buy-in amount in CHF, the share of individuals making a voluntary contribution (buy-in) and the log amount of voluntary contributions. For each variable we report the difference between the funds and a test statistics of a t-test. The sample includes all individuals who are between 25 and 65 years old that were insured in the pre-treatment period and have a non-zero buy-in potential. Data come from two Swiss pension funds.

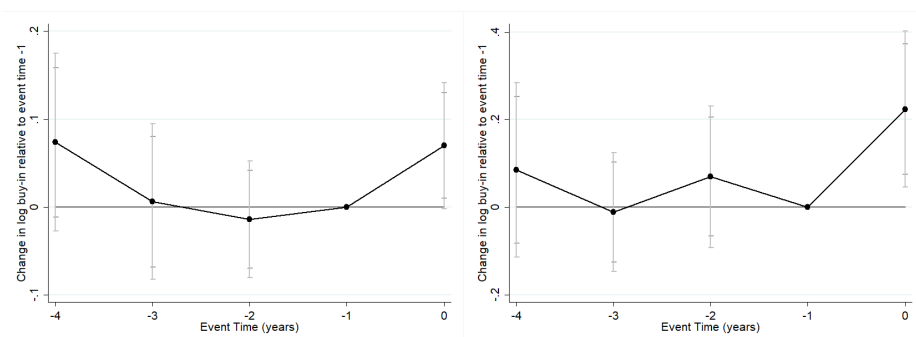
Introduction of pension app by fund To gain insights about the change in individual choices around the time of pension app introduction, we start estimating eq.(2) separately for pension fund A (introducing the app in 2017) and pension fund B (introducing the app in 2018). Because this descriptive analysis only exploits changes in contribution choices over time, we set $\theta_t = 0$. We estimate equation (2) for the probability to make a voluntary contribution. Panels (a) and (b) of Figure E1 report the marginal effects from a Probit model for fund A and fund B, respectively. The results show non significant estimates for the years before the individuals received the invitation letter to register in the app β_e $(e = -4, -3, -2)$, and in both pension funds a jump in the probability that insureds make a voluntary contribution in the year the pension app was introduced. Specifically, the contribution rate increases by around 1 and 2 percentage points among insureds in fund A and B, respectively. This findings are confirmed when we use the log of the contributed amount as dependent variable, as shown in Figure E2. Although there is no evidence of significant time trend in contribution rates in a given fund (β_e $(e = -4, -3, -2)$ are all statistically equal to zero), one needs to be cautious in interpreting these results as effects of introducing the app because they assume that there are no shocks occurring at the same time as the introduction of the app. To relax this assumption and exploit the variation in the roll-out of the pension app while conditioning on time fixed effects, we estimate our main event-study specification (2).



(a) Fund A (b) Fund B

Figure E1: Event study coefficients for the probability to do a buy-in by fund

Notes: The graph reports marginal effects of the event study coefficients from a Probit model based on the model in eq. (2) but excluding time fixed effects. Panel (a) shows the estimates for individuals insured in fund A and panel (b) shows the estimates for individuals insured in fund B. Dependent variable: buy-in dummy indicating a positive yearly contribution (buy-in) to the occupational pension fund. The event is receiving the invitation letter to for the first time. Event dummies are reported relative to year prior to event. The error bars show 90 and 95 percent confidence intervals for cluster robust standard errors at the individual level. Data from two Swiss pension funds from 2013-2018.



(a) Fund A (b) Fund B

Figure E2: Event study coefficients for the log buy-in amount by fund

Notes: The graph reports marginal effects of the event study coefficients from an OLS model based on the model in eq. (2) but excluding time fixed effects. Panel (a) shows the estimates for individuals insured in fund A and panel (b) shows the estimates for individuals insured in fund B. Dependent variable: log buy-in amount of yearly contributions (buy-in) to the occupational pension fund. The event is receiving the invitation letter to for the first time. Event dummies are reported relative to year prior to event. The error bars show 90 and 95 percent confidence intervals for cluster robust standard errors at the individual level. Data from two Swiss pension funds from 2013-2018.

Table E2: Static event study (ES) & DiD specifications for ITT effect

	Buy-in indicator				Log contributions	
	ES		DiD		ES	DiD
	(1)	(2)	(3)	(4)	(5)	(6)
	Probit	LPM	Probit	LPM	OLS	OLS
Post*Fund	0.0180**	0.0145**	0.0155*	0.0137*	0.137**	0.124*
	(0.00846)	(0.00665)	(0.00879)	(0.00728)	(0.0641)	(0.0702)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	15355	15478	11279	11364	15478	11364

Notes: Difference in differences estimates based on eq. 3. The table reports marginal effects from a Probit model in Column (1) and (3), and OLS estimates in Columns (2), (4), (5) and (6). Specifications (1), (2) and (5) are estimated with the entire sample whereas specifications (3), (4) and (6) are estimated with the restricted sample before the year 2018. Dependent variable in (1)-(4): buy-in dummy indicating a positive yearly contribution (buy-in) to the occupational pension fund. Dependent variable in (5) and (6): log amount of voluntary contributions to the occupational pension fund. Estimates are conditional on fund, year, gender, and marital status fixed effects. Moreover, all specifications control for second order polynomial of age, for log wage and for log tenure. Standard errors in parentheses are robust and clustered on the individual level. Data from two Swiss pension funds covering the years 2013–2019. The event defining the post dummy is receiving the invitation letter to register in the pension app for the first time.

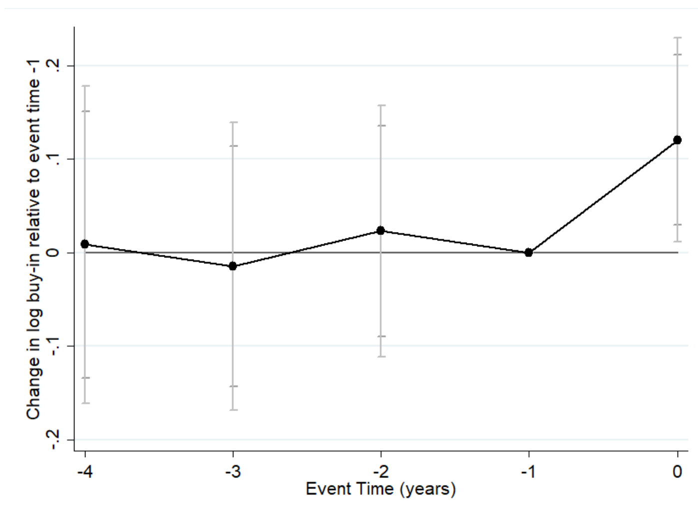


Figure E3: ITT: Event study coefficients (log buy-in amount)

Notes: The graph reports OLS coefficients of the event time dummies model based on the model in eq. (2). Dependent variable: log buy-in amount of yearly contributions (buy-in) to the occupational pension fund. The event is receiving the invitation letter to for the first time. Event dummies are reported relative to year prior to event. The error bars show 90 and 95 percent confidence intervals for cluster robust standard errors at the individual level. All estimates are reported in Table E3. Data from two Swiss pension funds from 2013-2018.

Table E3: ITT: Effect of invitation letter and app availability on voluntary contributions

	Buy-in indicator		**Log contributions**
	(1)	(2)	(3)
	Probit	LPM	OLS
eventtime -4	0.0044	0.0022	0.0085
	(0.0094)	(0.0090)	(0.0867)
eventtime -3	-0.0013	-0.0012	-0.0146
	(0.0089)	(0.0081)	(0.0784)
eventtime -2	0.0050	0.0027	0.0230
	(0.0078)	(0.0072)	(0.0687)
eventtime 0	0.0137^{**}	0.0130^{**}	0.1208^{**}
	(0.0068)	(0.0057)	(0.0555)
Year FE	Yes	Yes	Yes
Controls	Yes	Yes	Yes
Observations	11739	11824	11824

Notes: Event study estimates based on eq. 2. The table reports marginal effects from a Probit model in Column (1), and OLS estimates in Columns (2) and (3). Dependent variable in (1) and (2): buy-in dummy indicating a positive yearly contribution (buy-in) to the occupational pension fund. Dependent variable in (3): log amount of voluntary contributions to the occupational pension fund. Estimates are conditional on fund, year, gender, and marital status fixed effects. Moreover, all specifications control for second order polynomial of age, for log wage and for log tenure. Standard errors in parentheses are robust and clustered on the individual level. Data from two Swiss pension funds covering the years 2013–2018. The event is receiving the invitation letter to register in the pension app for the first time. Event dummies are relative to the year prior to event.

E.1 Heterogeneity analysis

We conduct the heterogeneity analysis both for the main event study design as well as conditioning on pension app registration status. The complete set of results is reported in Table E5 and Table E6. We focus in the main text on the probability to make a voluntary contribution. Figure E5 reports corresponding estimates for the log of contributed amount.

Gender First, we estimate eq.(3) separately for men and women in the sample. As depicted in panel (a) of Figure E4 and E5, we find that the average intention-to-treat effect is driven by male individuals, while women do not respond to the introduction of the pension app. The probability to make a voluntary buy-in following the intervention increases by around 2.44 percentage points among male insureds and that the contributions increase by around 17.9 percent.

As shown in panel (b) of Figure E4, we find no suggestive evidence of a response to sending the invitation letter, independently of the gender, among the insureds who do not register after receiving the letter. Using the sample of registered insureds, we find a large response to the possibility of accessing the app among men (7.9 percentage point increase in the probability to buy-in and 52.1 percent increase in the amount saved) but no significant response among women. A possible explanation for this evidence is that individuals' financial sophistication influences their ability to incorporate the information obtained through the pension app to take optimal retirement saving decisions, considering the gender gap in financial literacy extensively documented in the literature (see, e.g, Lusardi and Mitchell 2008).

Income As discussed in Section 1, the institutional setting provides fiscal incentives to make contributions to the occupational pension plans that increase with the worker's labor income, due to the progressive income taxation. Further, higher income earners may be less likely to be liquidity constrained. We split the sample in individuals below and above the median income in the sample (75'400 CHF).[48] As depicted in panel (c) of Figure E4, we observe larger responses to the introduction of the pension app among insureds with above-median income. The contribution rate among this group of workers increases by 2.71 percentage points following the introduction of the pension app, while the contributed amount increases by around 20.5 percent (see panel (c) of Figure E5). In contrast, we do not find a large contribution response among individuals with below-median income.

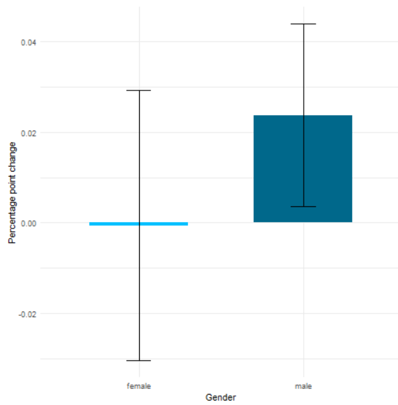
Regardless the income level, there is no response to the intervention among individuals who do not register in the pension app (see panel d of Figure E4). Among individuals

[48]This median wage is close to the median wage in Switzerland of 77'000 CHF in 2016 (data from Federal Statistical Office).

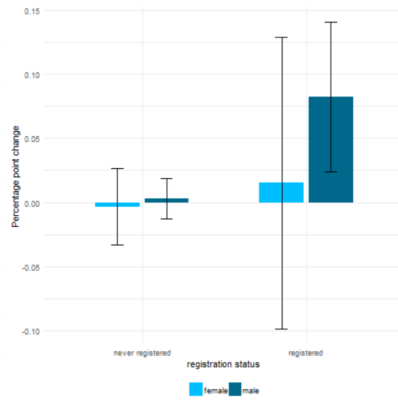
who do self-select into registering in the pension app, the analysis shows large contribution responses of individuals with above-median income, with the contribution rate increasing by around 8.75 percentage points, from a pre-intervention contribution rate of 8.6 percent. We do not find significant responses of individuals with below-median income even among individuals who register in the pension app, though the point estimate is higher compared to that obtained using the sample of below-median earners who do not access the app. This evidence suggests that the introduction of the pension application indeed influenced the retirement contribution behavior of individuals who, ex-ante, have more to gain from making an additional contribution to the occupational pension plan.

Potential buy-in Finally, we explore whether individuals respond differently to the introduction of the pension app depending on their potential of tax-favoured contributions.[49] Evidence that individuals with higher potential of tax-favoured contributions respond more to the introduction of the pension app would be consistent with our hypothesis that the introduction of the pension app induced a behavioral response through a reduction of the costs of information acquisition. The results show a large contribution response among individuals with above-median potential buy-in to wage ratio, with the probability to make a contribution increasing by around 3.1 percentage points following the introduction of the pension app, from a baseline contribution rate of 3.82 percent. We find no significant effect for individuals with a buy-in potential below the median (see panel (e) of Figure E4).

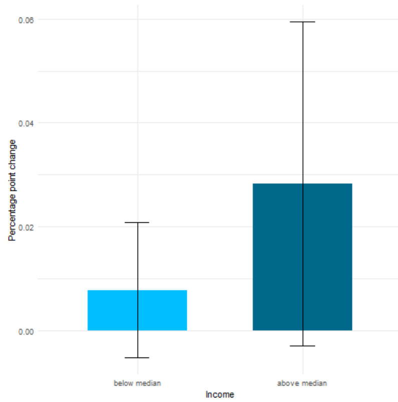
[49]The sample is divided between individuals with a potential buy-in to wage ratio below and above the distribution median.



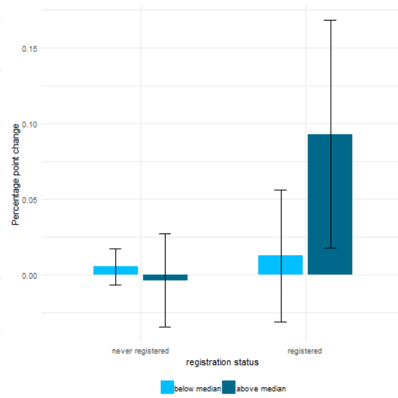
(a) gender



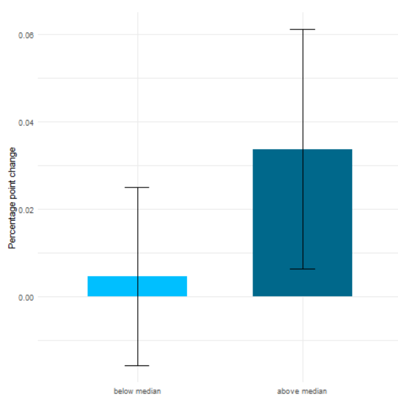
(b) gender & registration status



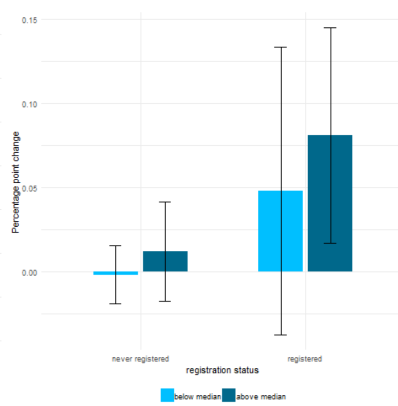
(c) income



(d) income & registration status



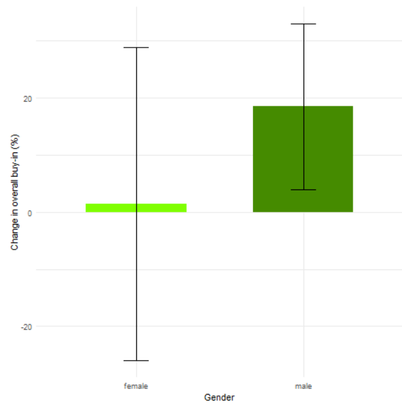
(e) buy-in potential



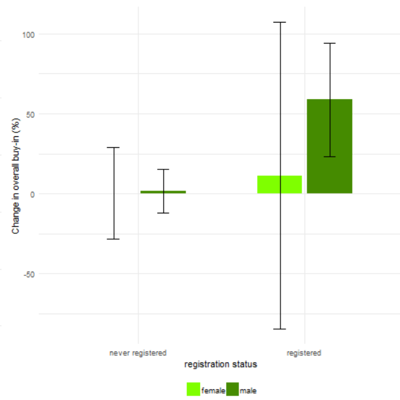
(f) buy-in potential & reg. status

Figure E4: Heterogeneity in intention-to-treat effect

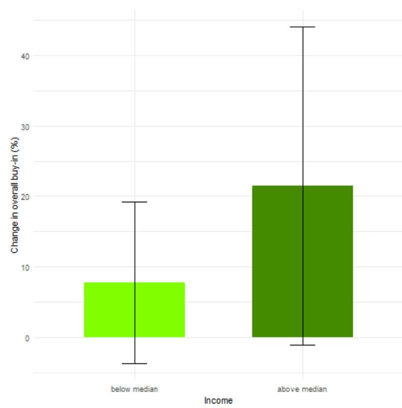
Notes: The graphs depict marginal effects of the difference in differences specification from a Probit model based on the model in eq. (3). The panels present different divisions of the sample along the dimensions gender, income and buy-in potential. Graphs on the left split the sample by one of these heterogeneity dimensions and graphs on the right divide the sample additionally by individuals' pension app registration status. Dependent variable: buy-in dummy indicating a positive yearly contribution (buy-in) to the occupational pension fund. The error bars show 95 percent confidence intervals for cluster robust standard errors at the individual level. Tables E5 and E6 report the estimates. Data from two Swiss pension funds from 2013-2019.



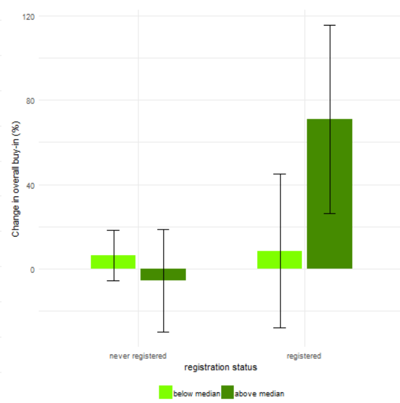
(a) gender



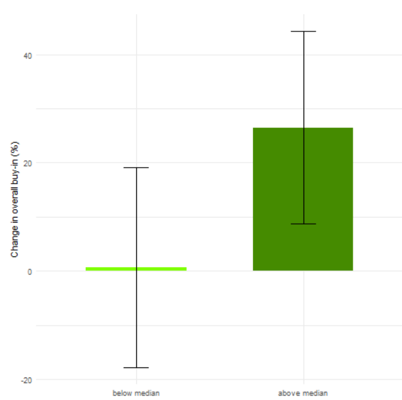
(b) gender & registration status



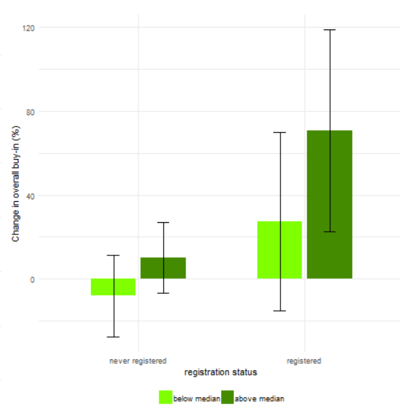
(c) income



(d) income & registration status



(e) buy-in potential



(f) buy-in potential & reg. status

Figure E5: Heterogeneity of treatment effect (log buy-in amount)

Notes: The graphs depicts OLS estimates of the difference in differences specification based on the model in eq. (3). The panels present different divisions of the sample along the dimensions gender, income and buy-in potential. Graphs on the left split the sample by one of these dimensions and graphs on the right additionally divide the sample by individuals' pension app registration status. Dependent variable: log buy-in amount of yearly contributions (buy-in) to the occupational pension fund. The error bars show 95 percent confidence intervals for cluster robust standard errors at the individual level. Tables E5 and E6 report the estimates. Data from two Swiss pension funds from 2013-2019.

Table E4: Heterogeneity by registration status

	Buy-in indicator				Log contributions	
	Never registered		**Registered**		**Never registered**	**Registered**
	(1) Probit	(2) LPM	(3) Probit	(4) LPM	(5) OLS	(6) OLS
eventtime -4	-0.0013	0.0007	0.0213	0.0127	-0.0109	0.1245
	(0.0089)	(0.0081)	(0.0284)	(0.0254)	(0.0791)	(0.2426)
eventtime -3	-0.0035	-0.0016	0.0008	0.0014	-0.0280	0.0415
	(0.0079)	(0.0076)	(0.0266)	(0.0217)	(0.0741)	(0.2119)
eventtime -2	0.0064	0.0043	0.0013	-0.0016	0.0340	-0.0055
	(0.0076)	(0.0074)	(0.0232)	(0.0182)	(0.0698)	(0.1767)
eventtime 0	-0.0004	-0.0001	0.0544***	0.0482***	-0.0086	0.4716***
	(0.0066)	(0.0058)	(0.0203)	(0.0146)	(0.0553)	(0.1449)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	9013	9111	2707	2713	9111	2713

Notes: Event study estimates based on eq. 2. The table reports marginal effects from a Probit model in Columns (1) and (3), and OLS estimates in Columns (2), (4), (5) and (6). Specifications (1), (2) and (5) are estimated with the restricted sample of individuals who never registered in the pension app whereas specifications (3), (4) and (6) are estimated with the restricted sample of individuals who have registered in the pension app. Dependent variable in (1), (2), (3) and (4): buy-in dummy indicating a positive yearly contribution (buy-in) to the occupational pension fund. Dependent variable in (5) and (6): log amount of voluntary contributions to the occupational pension fund. Estimates are conditional on fund, year, gender, and marital status fixed effects. Moreover, all specifications control for second order polynomial of age, for log wage and for log tenure. Standard errors in parentheses are robust and clustered on the individual level. Data from two Swiss pension funds covering the years 2013–2018. The event is receiving the invitation letter to register in the pension app for the first time. Event dummies are relative to the year prior to event.

Table E5: Heterogeneity in intention-to-treat effect

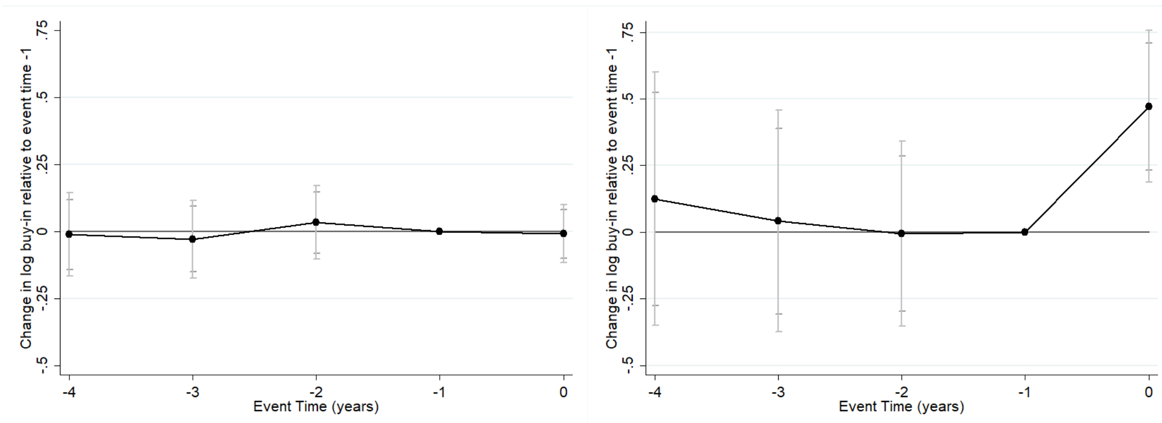
	Buy-in indicator		Contributed amount (log)	
	(1)	(2)	(3)	(4)
	Probit	Probit	OLS	OLS
(i) Gender	Female	Male	Female	Male
Post * Fund	0.0001	0.0239^{**}	0.0226	0.1866^{**}
	(0.0151)	(0.0103)	(0.1383)	(0.0742)
Year FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Observations	5637	9687	5716	9762
(ii) Income	below median	above median	below median	above median
Post * Fund	0.0080	0.0286^{*}	0.0797	0.2181^{*}
	(0.0066)	(0.0159)	(0.0582)	(0.1149)
Year FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Observations	7541	7810	7616	7862
(iii) Buy-in potential over wage	below median	above median	below median	above median
Post * Fund	0.0047	0.0339^{**}	0.0114	0.2645^{***}
	(0.0104)	(0.0139)	(0.0945)	(0.0905)
Year FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Observations	7703	7646	7738	7740
(iv) Age	below median	above median	below median	above median
Post * Fund	0.0135	0.0197	0.1059	0.1812^{*}
	(0.0092)	(0.0139)	(0.0736)	(0.1092)
Year FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Observations	7656	7638	7709	7731

Notes: Difference in differences estimates based on eq. 3. The table reports marginal effects from a Probit model in Column (1) and (2), and OLS estimates in Columns (3) and (4). Specifications (1) and (3) are estimated with the restricted sample of female individuals in panel (i), individuals with below median income in panel (ii), individuals with below median buy-in potential to wage ratio in panel (iii), and individuals with below median age in panel (iv) whereas specifications (2) and (4) are estimated with the restricted sample of male individuals in panel (i), individuals with above median income in panel (ii), individuals with above median buy-in potential to wage ratio in panel (iii), and individuals with above median age in panel (iv). Dependent variable in (1) and (2): buy-in dummy indicating a positive yearly contribution (buy-in) to the occupational pension fund. Dependent variable in (3) and (4): log amount of voluntary contributions to the occupational pension fund. Estimates are conditional on fund, year, gender, and marital status fixed effects. Moreover, all specifications control for second order polynomial of age, for log wage and for log tenure. Standard errors in parentheses are robust and clustered on the individual level. Data from two Swiss pension funds covering the years 2013–2019. The event defining the post dummy is receiving the invitation letter to register in the pension app for the first time.

Table E6: Effect heterogeneity with respect to gender, income and buy-in potential by registration status

	Buy-in indicator				Contributed amount (log)			
	Never registered		Registered		Never registered		Registered	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Probit	Probit	Probit	Probit	OLS	OLS	OLS	OLS
(i) Gender	Female	Male	Female	Male	Female	Male	Female	Male
Post * Fund	-0.0027	0.0032	0.0173	0.0831^{***}	0.0104	0.0172	0.1259	0.5937^{***}
	(0.0151)	(0.0080)	(0.0583)	(0.0298)	(0.1445)	(0.0698)	(0.4885)	(0.1825)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4608	6902	988	2776	4684	6971	1032	2791
(ii) Income	below median	above median	below median	above median	below median	above median	below median	above median
Post * Fund	0.0055	-0.0036	0.0129	0.0942^{**}	0.0657	-0.0552	0.0883	0.7171^{***}
	(0.0062)	(0.0157)	(0.0224)	(0.0386)	(0.0609)	(0.1245)	(0.1862)	(0.2293)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	6191	5311	1332	2478	6280	5375	1336	2487
(iii) Buy-in potential over wage	below median	above median	below median	above median	below median	above median	below median	above median
Post * Fund	-0.0016	0.0123	0.0485	0.0817^{**}	-0.0776	0.1025	0.2854	0.7131^{***}
	(0.0088)	(0.0150)	(0.0434)	(0.0327)	(0.0997)	(0.0852)	(0.2175)	(0.2470)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5861	5650	1815	1996	5917	5738	1821	2002

Notes: Difference in differences estimates based on eq. 3. The table reports marginal effects from a Probit model in Columns (1)-(4), and OLS estimates in Columns (5)-(8). Specifications (1), (3), (5) and (7) are estimated with the restricted sample of female individuals in panel (i), individuals with below median income in panel (ii), and individuals with below median buy-in potential to wage ratio in panel (iii) whereas specifications (2), (4), (6) and (8) are estimated with the restricted sample of male individuals in panel (i), individuals with above median income in panel (ii), and individuals with above median buy-in potential to wage ratio in panel (iii). Additionally, the sample is split into individuals that registered in the pension app (Columns (3), (4), (7), (8)) and individuals that never registered in the pension app (Columns (1), (2), (5), (6)). Dependent variable in Columns (1)-(4): buy-in dummy indicating a positive yearly contribution (buy-in) to the occupational pension fund. Dependent variable in Columns (5)-(8): log amount of voluntary contributions to the occupational pension fund. Estimates are conditional on fund, year, gender, and marital status fixed effects. Moreover, all specifications control for second order polynomial of age, for log wage and for log tenure. Standard errors in parentheses are robust and clustered on the individual level. Data from two Swiss pension funds covering the years 2013–2019. The event defining the post dummy is receiving the invitation letter to register in the pension app for the first time.



(a) never registered individuals

(b) registered individuals

Figure E6: Event study coefficients by registration status (log buy-in amount)

Notes: The graph reports OLS estimates of the event time dummies based on the model in eq. (2). Panel (a) shows the estimates for the restricted sample with individuals that never registered in then pension app and panel (b) shows the estimates for the restricted sample with only individuals that have registered in the pension app by mid 2019. Dependent variable: log buy-in amount of yearly contributions (buy-in) to the occupational pension fund. The event is receiving the invitation letter to for the first time. Event dummies are reported relative to year prior to event. The error bars show 90 and 95 percent confidence intervals for cluster robust standard errors at the individual level. All estimates are reported in Table E4. Data from two Swiss pension funds from 2013-2018.

E.2 Robustness: Placebo treatment

Table E7: Robustness of ITT: Placebo treatment

	Buy-in indicator		**Log buy-in amount**
	LPM	Probit	OLS
	(1)	(2)	(3)
Post * Fund	-0.00534	-0.00353	-0.0356
	(0.0117)	(0.0102)	(0.0968)
Year FE	Yes	Yes	Yes
Controls	Yes	Yes	Yes
Observations	8509	8582	8582

Notes: Difference in differences estimates based on eq. 3. The table reports marginal effects from a Probit model in Column (1) and OLS estimates in Columns (2) and (3). All specifications consider a placebo treatment of fund A in year 2016 and the years from 2017 are excluded from the sample. Dependent variable in (1) and (2): buy-in dummy indicating a positive yearly contribution (buy-in) to the occupational pension fund. Dependent variable in (3): log amount of voluntary contributions to the occupational pension fund. Estimates are conditional on fund, year, gender, and marital status fixed effects. Moreover, all specifications control for second order polynomial of age, for log wage and for log tenure. Standard errors in parentheses are robust and clustered on the individual level. Data from two Swiss pension funds covering the years 2013–2016.

F RCT: Experiment design and reminder letters

F.1 Experiment design

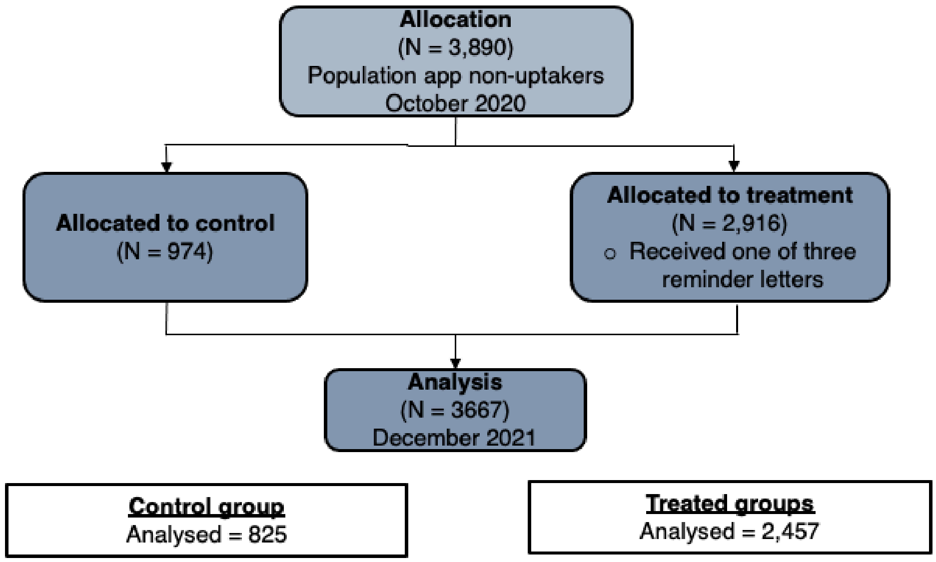


Figure F1: Experiment design

F.2 Reminder letter standard

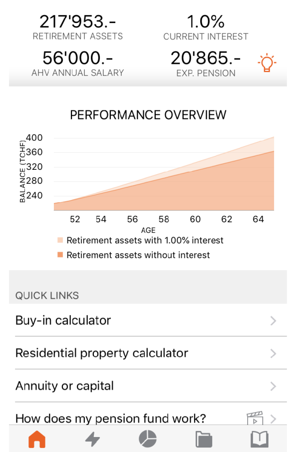
[redacted]

Personal / Confidential

Date: October 2020
Reference: 450.

Contact: [redacted]
Telephone:
Mail:

Do you know how high your pension benefits will be and how you can influence them?



Dear Mrs/Mr

The [redacted] creates an additional benefit for its insured with a unique app. Take pension provision into your own hands and benefit from the information advantages.

The app summarizes all important information on your pension situation: Your current insurance certificate, your expected pension benefits, your personal buy-in potential for additional savings contributions, your withdrawal options for the home ownership subsidy, the payment modalities upon retirement, and much more.

For example, do you know whether you will be able to maintain your accustomed standard of living after retirement? In Switzerland, the ratio of pension benefits from mandatory contributions to the last net wage is approximately 44% (OECD). It is therefore important to plan and act on your own.

Do your personal pension check with the app. Register and find out about your pension situation with the app for our insured customers!

Figure F2: Reminder letter without additional nudge

F.3 Reminder letter with taxation nudge

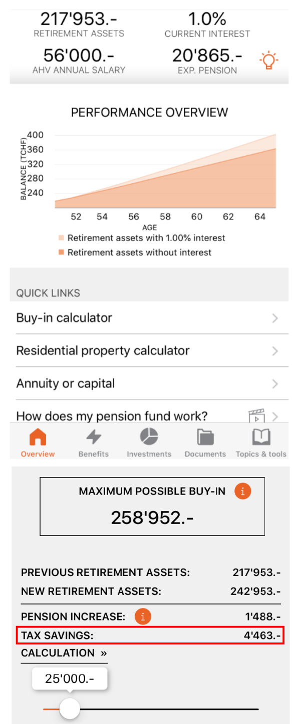
[redacted]

Personal / Confidential

Date: October 2020
Reference: 450.

Contact: Telephone: Mail: [redacted]

Do you know how high your pension benefits will be and how you can influence them?



Dear Mrs/Mr

The [redacted] creates an additional benefit for its insured with a unique app. Take pension provision into your own hands and benefit from the information advantages.

The app summarizes all important information on your pension situation: Your current insurance certificate, your expected pension benefits, your personal buy-in potential for additional savings contributions, your withdrawal options for the home ownership subsidy, the payment modalities upon retirement, and much more.

For example, do you know whether you will be able to maintain your accustomed standard of living after retirement? In Switzerland, the ratio of pension benefits from mandatory contributions to the last net wage is approximately 44% (OECD). It is therefore important to plan and act on your own.

Or do you know that voluntary savings contributions (buy-ins) can be fully deducted from income tax? Find out how big your buy-in potential is and how much taxes you could save through voluntary contributions.

Do your personal pension check with the app. Register and find out about your pension situation with the app for our insured customers!

Figure F3: Reminder letter with taxation nudge

F.4 Reminder letter with transaction cost nudge

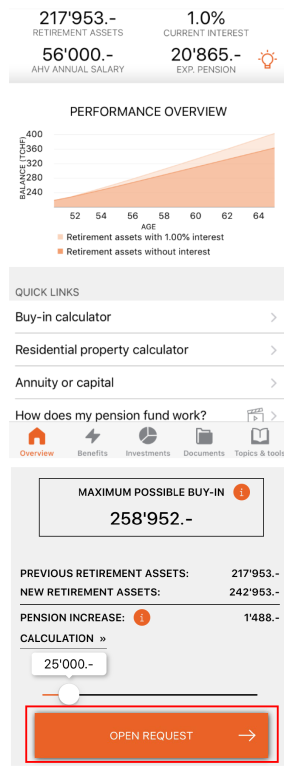
[redacted]

Personal / Confidential

Date: October 2020
Reference: 450.

Contact:
Telephone:
Mail: [redacted]

Do you know how high your pension benefits will be and how you can influence them?



Dear Mrs/Mr

The [redacted] creates an additional benefit for its insured with a unique app. Take pension provision into your own hands and benefit from the information advantages.

The app summarizes all important information on your pension situation: Your current insurance certificate, your expected pension benefits, your personal buy-in potential for additional savings contributions, your withdrawal options for the home ownership subsidy, the payment modalities upon retirement, and much more.

For example, do you know whether you will be able to maintain your accustomed standard of living after retirement? In Switzerland, the ratio of pension benefits from mandatory contributions to the last net wage is approximately 44% (OECD). It is therefore important to plan and act on your own.

In addition, the [redacted] app considerably simplifies the process of making voluntary contributions. See for yourself how easy it is to submit an application with the insured app.

Do your personal pension check with the app. Register and find out about your pension situation with the app for our insured customers!

Figure F4: Reminder letter with transaction cost nudge

G Experimental results

Table G1: Attrition by treatment status

	Attrition indicator	
	LPM	LPM
	(1)	(2)
Treatment indicator	-0.0028	
	(0.0053)	
Treatment 1: letter base		-0.0031
		(0.0064)
Treatment 2: letter tax		0.0020
		(0.0065)
Treatment 3 : letter transaction cost		-0.0074
		(0.0062)
Year dummy 2021	-0.0384***	-0.0385***
	(0.0044)	(0.0044)
Constant	0.0594***	0.0594***
	(0.0057)	(0.0057)
Observations	7386	7386

Note: The table reports results for a linear probability model. Dependent variable is an indicator whether an individual had dropped out of the sample in 2020 or 2021 respectively. The treatment indicator in Column (1) corresponds to a dummy for receiving any reminder letter. In Column (2) the treatment variables are binary variables for receiving a certain type of reminder letter as the treatment. Robust standard errors in parentheses. Data from two Swiss pension funds for the years 2020 and 2021.

Table G2: Balance of observables by reminder letter between treatment and control group

	Control Mean	Treatment Mean	Diff	Diff SE	t-test p-value
		Treatment: Standard			
Age	43.284	43.866	-0.583	0.484	0.229
Gender (male)	0.656	0.647	0.009	0.022	0.676
Wage (CHF)	78'192	77'666	526	1271	0.679
Pension wealth (CHF)	94'008	96'451	-2363	5510	0.668
Buy-in potential	84'021	89'647	-5626	4806	0.242
Tenure (years)	6.875	6.894	-0.018	0.358	0.960
Single	0.462	0.460	0.002	0.023	0.916
Observations	974	966			1940
		Treatment: Tax			
Age	43.284	43.476	-0.192	0.480	0.689
Gender (male)	0.656	0.655	0.001	0.021	0.979
Wage (CHF)	78'192	76'674	1518	1203	0.207
Pension wealth (CHF)	94'008	93'550	539	5550	0.923
Buy-in potential	84'021	83'215	806	4605	0.861
Tenure (years)	6.875	6.791	0.084	0.358	0.814
Single	0.462	0.502	-0.040	0.023	0.077
Observations	974	984			1958
		Treatment: Transaction costs			
Age	43.284	43.699	-0.415	0.477	0.384
Gender (male)	0.656	0.660	-0.004	0.022	0.838
Wage (CHF)	78'192	79'027	-834	1289	0.518
Pension wealth (CHF)	94'008	100'407	-6'319	5882	0.283
Buy-in potential	84'021	88'845	-4823	4884	0.323
Tenure (years)	6.875	6.984	-0.109	0.356	0.761
Single	0.462	0.480	-0.018	0.023	0.419
Observations	974	966			1940

Notes: The table presents means, differences and their standard errors and p-values of a t-test comparing the group means for a selection of observables in our sample. This table compares the control group which did not receive a reminder to all individuals that have received a reminder.

Table G3: Effect of reminder letters on registration status

	Indicator app registration	
	Any letter	By letter type
	(1)	(2)
Treatment	0.0684***	
	(0.0077)	
Treatment: letter base		0.0746***
		(0.0104)
Treatment: letter tax		0.0695***
		(0.0101)
Treatment: letter transaction		0.0611***
		(0.0101)
Controls	Yes	Yes
Observations	6956	6956
Mean control group	0.073	0.073

Notes: The table reports effects from a linear probability model and reports marginal effects of the treatment indicators on the registration status of individuals in the pension app. Dependent variable in all specifications is a binary indicator for insureds that have registered in the pension app in 2020 or 2021. Column (1) report the estimates for a binary treatment indicator and column (2) for an indicator by letter as explanatory variable. Both specifications include control variables gender, age, age squared, log income, marital status, fund membership and tenure in the firm. Robust standard errors are reported in parentheses. Data from two Swiss pension funds for the years 2020 and 2021.

Table G4: Effect of different information nudges on contributions

	Buy-in indicator					
	Standard		Tax		Transaction costs	
	ITT	LATE	ITT	LATE	ITT	LATE
	(1a)	(2a)	(3a)	(4a)	(5a)	(6a)
Treatment	-0.0020	-0.0118	0.0003	0.1018	0.0100*	0.3817**
	(0.0048)	(0.0730)	(0.0049)	(0.1188)	(0.0058)	(0.1835)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1754	1751	1752	1734	1766	1754
Mean control group	0.0131	0.0131	0.0131	0.0131	0.0131	0.0131

	Log buy-in amount					
	(1b)	(2b)	(3b)	(4b)	(5b)	(6b)
Treatment	-0.0267	-0.2161	-0.0065	0.8307	0.1008*	3.9351**
	(0.0487)	(0.7302)	(0.0488)	(1.1421)	(0.0603)	(1.8824)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1754	1751	1752	1734	1766	1754
Mean control group	0.132	0.132	0.132	0.132	0.132	0.132

Notes: Estimated marginal effect of the treatment indicator from a linear probability model are reported. Dependent variable in the panel above is a binary indicator for insureds that have made a buy-in to their pension fund after the treatment in 2020. Dependetn variable in the lower panel is the log of contributions in the form of a buy-in. Columns (1) and (2) report estimates for the control group and the treatment group that received the standard letter, Columns (3) and (4) report estimates for the control group and the treatment group that received the additional taxation nudge and Columns (5) and (6) report estimates for the control group and the treatment group that received the additional transaction cost nudge. Columns (1), (3) and (5) present the results for the intention-to-treat effect and columns (2), (4) and (6) the estimates of the local average treatment effect from a 2SLS-IV model using Wooldridge's two step approach. All specifications control for insureds' gender, age, age squared, log income, marital status and fund membership. Robust standard errors are reported in parentheses.

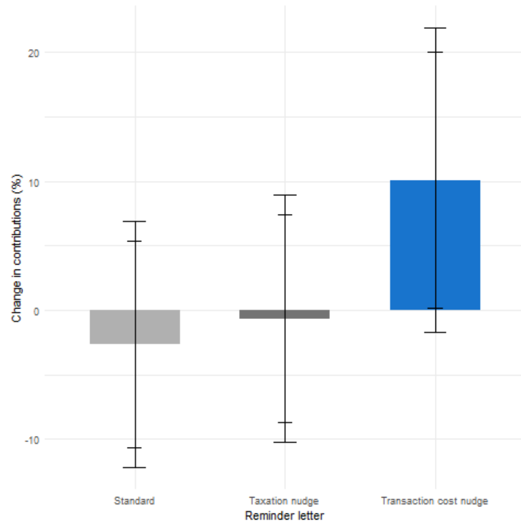


Figure G1: ITT of reminder letter on contributions by letter type

Notes: The graph plots the estimates of the intent-to-treat effect of the reminder letters by letter type on contributions. The corresponding results for the probability to contribute are depicted in Figure 6. The bars represent the effect of the pension app compared to the control group with 90 percent and 95 percent confidence intervals. Results are reported in Table G4. Dependent variable is the log amount of voluntary contribution after having received the reminder letter until the end of the year 2020. Data from two Swiss pension funds for the year 2020.

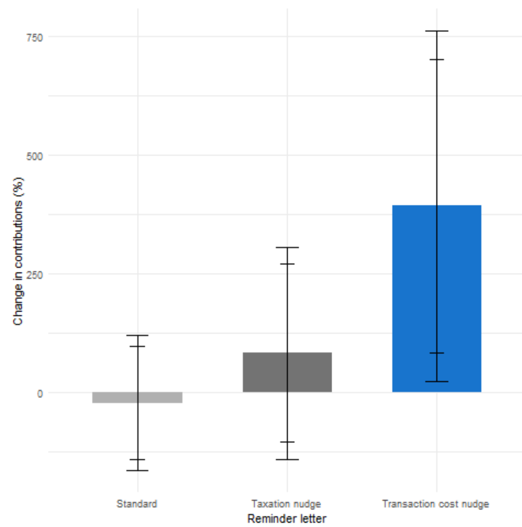


Figure G2: LATE of pension app on contributions by letter type

Notes: The graph plots the estimates of the local average treatment effects by letter type on contributions. The corresponding results for the probability to contribute are depicted in Figure **??**. The bars represent the effect of the pension app compared to the control group with 90 percent and 95 percent confidence intervals. Results are reported in Table G4. Dependent variable is the log amount of voluntary contribution after having received the reminder letter until the end of the year 2020. Data from two Swiss pension funds for the year 2020.

H Sample characteristics

Table H1: Summary Statistics - Comparison Sample and Switzerland

	Sample	**Switzerland**
Gender (male in %)	60.9	52.9 (in economic active population) 58.9 (new 2nd pillar recipients 2018)
Age (average)	42.75	41.8
Wage (median, CHF)	88'006	78'024

Notes: The table shows how selected summary statistics for the final sample with insureds from the two pension funds in the year 2016 compares to the corresponding values for Switzerland as a whole. We report the share of male individuals in the sample and in the economic active population respectively among new recipients of a occupational pension, the average age, and the median wage in CHF. Data from two Swiss pension funds and the Federal Statistical Office Switzerland.