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Personalized Digital Information and Tax-favoured Retirement Savings: Quasi-experimental Evidence from Administrative Data

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Abstract

This paper studies the impact of making personalized digital information available through a pension app on contributions to tax-favored retirement accounts. Using Swiss administrative pension fund data, we document limited take-up of fiscal incentives for retirement savings. Exploiting the staggered introduction of the pension app across occupational pension funds, we show that its availability increases individual tax-favored contributions. Men and higher-income earners are more likely to access the digital environment and respond to its introduction. These findings suggest that providing access to a pension app reduces information and transaction costs and facilitates the take-up of financial incentives for retirement saving.

Keywords: Defined contribution plans, Fiscal incentives, Pension app, Savings
JEL Codes: D14, G51, H31, H55

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1 Introduction

The demographic transition has prompted the reform of the social security system in different countries, with the phase-in of defined contribution schemes that are often, at least partially, non-mandatory. This makes individuals increasingly responsible for their retirement preparedness. In this context, several countries have introduced fiscal incentive schemes to promote additional voluntary retirement savings. However, a large literature has documented that many individuals take poor decisions when saving for retirement and fail to take-up the fiscal benefits that they are entitled to (Madrian and Shea, 2001; Currie, 2006; Saez, 2009; Choi et al., 2011). Possible explanations for this phenomena include limited pension knowledge and financial literacy, low program awareness and program complexity (Mastrobuoni, 2011; Lusardi and Mitchell, 2014; Bhargava and Manoli, 2015; Liebman and Luttmer, 2015). Based on administrative data from two Swiss pension funds, this paper provides evidence that providing access to personalized digital information through a pension app increases tax-favored contributions to occupational pension plans.

We first document some key facts in the administrative data about individuals' retirement preparedness and contribution behavior, with a focus on the extent with which individuals are taking advantage of the fiscal incentives to save for retirement brought about the Swiss pension system. These fiscal benefits are substantial. Individuals can save up to 47% 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). We then study the consequences of making a new digital pension application available to individuals insured with two occupational pension funds. The pension app is linked to the individual retirement saving account and provides information on the current account balance, the expected occupational pension benefits under the current contribution scenario, the individual potential for tax-favored contributions, the changes in expected pension wealth at retirement implied by alternative contribution strategies as well as the corresponding monetary savings in income taxes. Further, it allows to directly apply for these benefits through the app, thus simplifying the contribution process. The insured only needs to register in the app with a personalized log-in sent by her pension fund with an invitation letter. As 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 information tools linked to the individuals' retirement saving accounts to help them plan for retirement, it is crucial to understand how saving choices respond to the availability of this new type of information provision.[1] While few recent studies have investigated the

[1]An online platform, the "Digitale Rentenübersicht", is planned to be introduced in Germany in

effect of financial incentives (Bauer et al., 2018) and tailored pension information (Dinkova et al., 2018) on the navigation behaviour in digital pension environments, no evidence has been provided on the effect of introducing such tools on retirement saving behavior.

Because acquiring pension-related information and accumulating the relevant knowledge is costly, individuals might find it optimal to take uninformed decisions (Caplin and Dean, 2015; Jappelli and Padula, 2013; Lusardi et al., 2017). We hypothesize that individuals have limited knowledge or attention about the pension rules and the fiscal incentives for voluntary retirement savings, and that the pension application reduces the information and direct transaction costs that individuals need to sustain to take informed saving decisions. Our main objective is then to provide an estimate for the impact of providing individuals with the possibility to use the pension app on voluntary savings to their occupational pension plans. Linking pension app registration data to the administrative data from the pension funds, we also wish to characterise the demand for digital retirement-related information and provide suggestive evidence on the behavioral mechanism underlying the saving response to its introduction.

Our identification strategy for the effect of providing access to the pension app uses the staggered roll-out of the pension app across the two pension funds over time. We adopt an event study design that exploits the circumstance that, while the individuals insured with one occupational pension fund were granted access to the pension app in 2017, the individuals insured with the second fund (fund B) 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.

The administrative data include error-free information on individuals' 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 for the years 2013 to 2019. Further, the data include informa-

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/.)

tion on basic socio-economic characteristics. First, we document a large heterogeneity in the replacement rates from second pillar wealth for individuals with similar income levels, suggesting the importance of additional voluntary contributions for the retirement preparedness of (some) individuals in our sample. We also document substantial potential for tax-favored savings to occupational pension plans. Our results show an increasing age pattern of tax-favoured contribution potential over the working life, with individuals having the possibility to make contributions corresponding to twice their labor income close to the normal retirement age. Second, we show a hump-shape age profile in the share of individuals making a voluntary contribution to their occupational pension plan over the working life. Finally, male, higher-income earners are found to be more likely to register in the pension app.

Our main finding is that providing access to the pension app has an important effect on retirement saving decisions. The overall probability to make a tax-favoured contribution to the occupational pension fund increases by around 1.8 percentage points from an average pre-treatment voluntary contribution rate of 2.82% following the introduction of the pension app. Using pension app registration data, we also provide suggestive evidence that the average intention-to-treat effect on contribution behavior is driven by those individuals who eventually register in the pension app. Together, these finding suggest that the pension application reduces the information and transactions costs required to make informed retirement saving decisions. Further, we find substantial effect heterogeneity, with contribution decisions of men, higher income earners and individuals that have accumulated larger potential of tax-favoured contributions responding more to the introduction of the pension app.

This papers contributes to the large literature that considers explanations for the poor decisions that many individuals take when planning for retirement. By showing that the introduction of enhanced pension-related information through a pension app affects behavior, our findings provide further evidence that individuals are imperfectly informed, or inattentive, about retirement-related issues.

Our work is especially 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. The evidence on the effect of providing personalized retirement-related information is mixed. Mastrobuoni (2011) finds that information about future social security benefits has a positive impact on knowledge but not on saving 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 savings (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. We contribute to the literature by showing that providing the possibility to access personalized pension-related information through a pension app induces substantial retirement saving responses. We also characterize the demand for such digital retirement-related information. Further, by using pension app registration data, this paper provides suggestive evidence on the underlying behavioral mechanism. It points towards the importance of information and transactions costs faced by individuals to make optimal retirement saving decisions, rather than lack-of salience of retirement planning. Finally, it shows that sizable retirement contribution responses can be achieved with a relatively inexpensive intervention (i.e., sending an invitation letter to register in a pension app, once this is developed) that can be easily scaled to the population of workers insured with an occupational pension fund.

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 savings in Switzerland using administrative pension fund data. Second, we show that the take-up of financial incentives for retirement savings increases in response to the introduction of personalized digital information through a pension app.

The remainder of the paper is organized as follows. In section 2, we describe the institutional background and the intervention. Section 3 discussed our identification strategy for the effet of providing access to the pension app on tax-favoured contributions. In Section 4, we present the administrative pension fund data descriptive evidence on tax-favoured saving potential, heterogeneity in retirement preparedness, determinants of voluntary contributions and demand for digital retirement-related information. Section 5 presents the results on the effects of introducing the pension app. The final section discusses conclusions.

2 Institutional Setting

2.1 The Swiss pension system

Switzerland has a three pillar social security system combining defined benefits and defined contribution schemes.[2] The social security system in Switzerland has strong parallels to the social security system in the United States with its combination of a capped defined benefits

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

scheme and substantial defined contribution schemes.

The Swiss Old Age Insurance (AHV) - **first pillar** - is a standard pay-as-you-go redistributive scheme aiming at securing a minimum living standard for the elderly (it resembles then the Old-Age, Survivors, and Disability Insurance (OASDI) in the US). Contributions are mandatory and paid as a fixed percentage of labor income (8.7 %). Pension benefits are calculated as a combination of years of contribution and average labor income but are subject to an upper limit for retirement benefits.[3] Consequently, the first pillar provides low replacement rates at retirement for individuals with higher income levels. For example, the replacement rate from the first pillar cannot exceed 28 % for an individual earning 100'000 CHF a year before retirement.

Occupational pension plans - **second pillar** - are defined contribution schemes that aim at allowing insured individuals to maintain living standards during retirement. In 2017, 1'643 pension funds in Switzerland managed 894.3 billion CHF in assets, corresponding to about 133 % of Swiss GDP.[4] The second pillar is mandatory for employees with an income above 21'330 CHF (around 50% of the minimum annual wage for a full time employee) and shows similarities to the 401(k) plans in the United States. There are minimum contributions for different age brackets that are at least matched by employers. Contribution rates range from 7% at 25 years of age to around 18% before retirement. Contributions are credited to an individual retirement account within a pension fund.[5] The second pillar complements the capped survivors and disability insurance provided by the first pillar. At retirement, the accumulated capital is paid out either as a lump-sum, an annuity or a combination of the two.[6]

The last component of the Swiss pension system are voluntary private retirement accounts - **third pillar 3a**. They allow for limited tax-favoured contributions of up to 6'826 CHF per year (year 2019) to a special savings account at a bank or insurance company.[7] The accumulated capital is paid out as lump sum at retirement.

[3] Single individuals that contributed at least 40 years receive not more than 2'370 CHF per month. Married couples receive not more than 3'555 CHF jointly.

[4] Data from Federal Statistical Office.

[5] Pension funds have to guarantee a minimum interest rate on capital. In 2020, this is 1%. 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.

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

[7] 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.

2.2 The tax-favored voluntary buy-in option

Besides making mandatory contributions to their occupational pension plan as outlined above, working individuals have the possibility to make additional voluntary contributions. Each year, they can choose to make contributions for a maximum equal to their *buy-in potential*. This is a function of the individual's contribution history and her current income level. 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. The buy-in potential can then arise, for instance, from transitions to higher paying jobs, employment breaks or unemployment spells. Especially due to typically increasing salaries over the working life, the buy-in potential can become substantial.

Consider for example a 50 years old individual who had a constant income of 100'000 CHF since the age of 25. A rise in the wage to 110'000 CHF translates to a buy-in potential of 21'500 CHF that the individual could now voluntarily contribute additionally to her occupational pension fund.[8] If the income declines again to 100'000 CHF or below, the potential buy-in would become zero again. Overall, individuals in Switzerland transferred in 2017 5.6 billion CHF with the buy-in option to their second pillar retirement accounts.

Fiscal incentives for voluntary retirement savings In the Swiss pension system, individuals can access several fiscal benefits by making voluntary contributions to their occupational pension plans:[9] (i) contributions are deductible in full from the 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.[10] Tax rates differ between cantons and municipalities. Nonetheless, all cantons have progressive tax rates. (iii) returns from retirement accounts are tax-exempt.

The accumulated pension wealth is taxed when paid out at retirement. Annuities are taxed as income while a special tax applies to lump-sum withdrawals at retirement.[11].

Overall, the Swiss tax system creates substantial fiscal incentives to make additional

[8] The figures are calculated as the difference between the mandatory contributions to the occupational pension fund for the two income levels.

[9] 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.

[10] Individuals in Switzerland are subject to both income and wealth taxation. Taxation on wealth is levied by cantons and municipalities. Overall, wealth taxes accounted for 9,2 % of overall tax revenue of cantons and municipalities in 2015 (data from the Swiss Federal Tax Administration).

[11] The special tax on lump-sum withdrawals is calculated in all cantons regardless of the personal income and wealth situation. Tax rates vary depending on the canton and municipality of residence (Lichtensteiger and Schubiger, 2019)

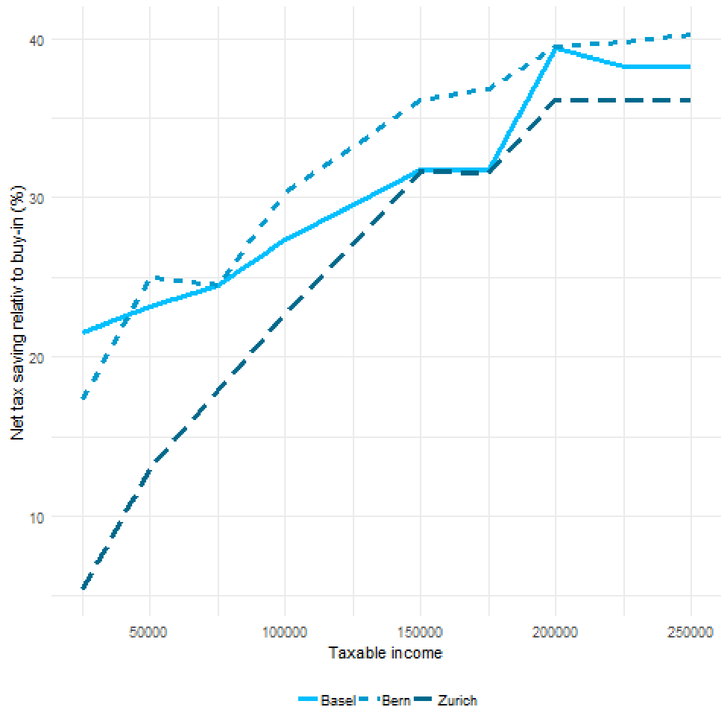


Figure 1: Illustration of tax benefits from a voluntary buy-in

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.

voluntary savings for retirement. Figure 1 depicts the net tax savings from a 10'000 CHF buy-in by income level, and separately for individuals living in Zurich, Bern and Basel in the year 2019.[12] The simple calculation shows indeed that the net tax savings range between around 10% (at the bottom of the income distribution) and 40% (at the top of the income distribution) of the contributed amount.[13] The implicit additional rate of return from the buy-in compared to an investment for example in the stock market depends on an individual's marginal tax rates, the timing of the buy-in, and the assumed returns of the

[12]Local administrative areas in Switzerland (cantons) have large autonomy in setting tax rules. As a result, the labor income tax schedule varies significantly across cantons. 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.

[13]These figures 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% of the present value of contributions for an average earner, and up to 47% for high income individuals.

investments.[14] The institutional setting provides then especially large fiscal incentives to make voluntary retirement savings for higher income earners due to the progressive labor income tax schedule.

2.3 Pension funds background

We collaborated with two pension funds that insured 6'100 employees from around 500 firms in the year 2017. 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, with a coverage ratio above 100 % (110 % and 104 %) at the end of 2017. Both pension funds are managed by the same administrative company. Contribution rates, matching formula, and conversion rates are typical for pension funds in Switzerland. Fund A had a conversion rate of 5.8% and fund B of 5.9% in the year 2017.[15]

2.4 The intervention: digital pension application

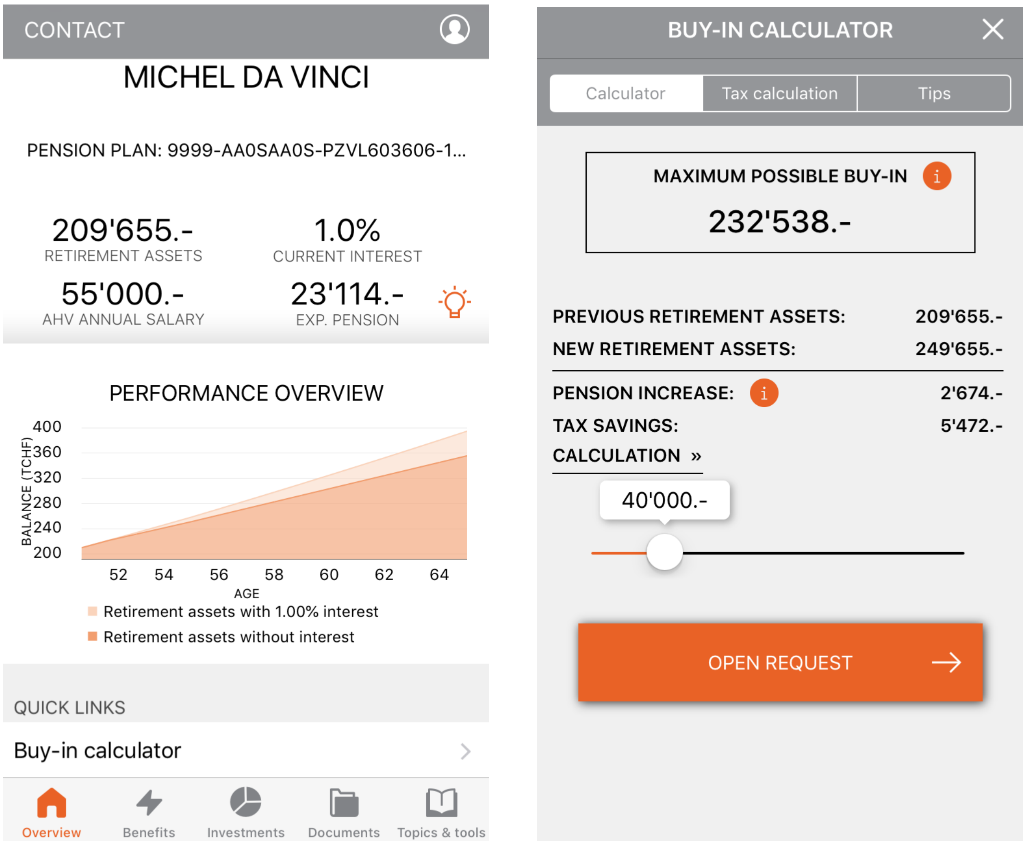
Baseline pension communication strategy Until 2017, these two pension funds adopted a pension communication strategy that is typically employed by occupational pension funds in Switzerland. A letter is sent annually at the insured's residence address with some information on the individual's retirement account. The letter includes information on the current balance of the retirement account, projections for retirement benefits under the current mandatory contribution plan and the individual's buy-in potential. If an individual decides to buy-in, 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.

Information provision through the pension application The company managing the two pension funds developed a pension application and made it available to their insureds, with the aim of helping them obtain information, plan and take decisions to plan for retirement. This online tool is similar to an online banking account, and makes use of the individuals' current account balance and employment data to provide personalized information to the user. The type of information provided by the pension application goes beyond that included in the annual letter and covers different aspects that are relevant for retirement

[14] 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 % (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

[15] The median conversion rate in Switzerland was 6% 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.

planning. First, it provides general information about the pension system itself, individual choice options and on the performance (return) of the pension fund in the last years. Second, it informs insured individuals about the status quo of their personal pension wealth in the second pillar: 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.[16] Panel (a) of Figure 2 shows a screenshot of the home screen of the application.



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

Figure 2: The pension application

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.

Third, as shown in panel (b) of Figure 2, the pension app allows to interactively simulate (through the usage of a slider) the implications of alternative additional voluntary contribution strategies. The app then simulates the changes in expected pension wealth at retirement

[16]This second part of the information is then similar, though more easily accessible, to that provided through the annual letter.

(and annual pension benefits) implied by any given amount of voluntary contributions made at the time of usage. Most importantly, the app calculates and informs about the monetary savings in income taxes that can be achieved with a voluntary contribution today. Fourth, the app allows to interactively simulate the projected retirement wealth with different interest rates, this way highlighting the role of interest compounding. Finally, the digital application significantly simplifies the process of making voluntary contributions, allowing to apply for additional contributions directly with a simple “click” on the “open request” button (see panel (b) of Figure 2).

The pension app does not track individual user behavior. However, we can observe aggregate usage statistics.[17] As shown in Figure A1 in Appendix A, the buy-in calculator is the most frequently used tool within the pension app. In 65.8% of all log-ins to the pension application, users have used this tool at least once. The standard information letter was accessed in 4.3% of log-ins. In 3.4 % of log-ins, individuals actually sent a request to do a voluntary buy-in.

Pension app and retirement planning Overall, the digital application significantly lowers the individual costs of accumulating the relevant knowledge to make informed retirement planning decisions compared to the letter typically sent once a year to individuals insured with an occupational pension plan. In fact, provided with the summary statistics included in the annual letter, the insured needs to know the interest rate she is earning on occupational pension wealth and the conversion rate at retirement, as well as the concept of compound interest rate (Lusardi and Mitchell, 2014), to project how an additional contribution today reflects into higher expected pension benefits once retired. Further, to estimate the tax benefits from a given contributed amount, the insured needs to be aware of the presence of the tax incentives (Bhargava and Manoli, 2015) as well as her marginal income tax rate.

Further, the app highlights the possibility for the insured to make a buy-in and reduces the direct transaction costs for making the voluntary contribution. Absent the app, the process is complex, especially compared to the third pillar option that is usually integrated and accessible in an individual’s online banking account.

In the presence of these information and transaction costs, individuals may find it optimal not to make voluntary retirement savings and access the fiscal benefits they are entitled to (Caplin and Dean, 2015). Our hypothesis is that individuals have limited knowledge or attention about the pension policy rules and the fiscal incentives for voluntary retirement savings they introduce. Then, providing individuals with facilitated access to retirement-related information through the pension app will induce a behavioural response.

[17]We use data for iOS devices. (April 2018 - April 2019).

2.5 Phasing in of the pension application

The two pension funds (fund A and fund B) invited their insureds to access the pension app through a letter sent by regular mail at the insured's residence. The two funds sent a letter to their insureds with information that a new pension app is available.[18] 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. However, the company managing the two pension funds decided to make the pension app available to the insured individuals using a staggered roll-out. The timeline of the natural experiment is depicted in Figure 3. 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.

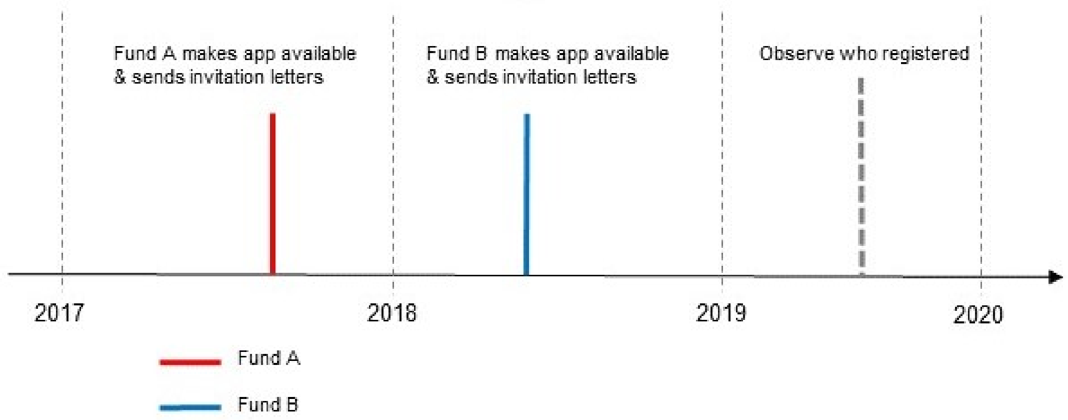


Figure 3: Timeline of introduction of application
Notes: The figure shows schematically the timeline of the introduction of the pension app and the timing of sending the invitation letters. Source: Authors.

This implies that individuals insured with fund A had the possibility to access the retirement-related information through the pension app before the end of the fiscal year 2017, in contrast to those insured with fund B. Importantly for our empirical strategy, in the pre-intervention period the overwhelming majority of voluntary contribution decisions were taken by insured individuals in the months of November and December.[19], as shown in Figure C1 in Appendix C.

[18] A copy of the letters sent by the two funds is included in Appendix A.
[19] 70 % of all voluntary buy-ins are made in December, 14 % in November and 5 % in October. All the earlier months have shares below 3 %.

The differential timing of the introduction of the pension app across the two funds was decided by their management solely based on administrative considerations. After having received the invitation letter, insured individuals could choose to download the pension application and register using the personalized log-in code included in the invitation letter. We observe who had registered to the pension app in June 2019.

3 Identification Strategy

The availability of the pension app allows individuals insured with the two funds to access enhanced pension-related information in a digital, interactive way. It thus has the potential to reduce information and transaction costs that individuals need to pay to make informed retirement planning decisions. The objective 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 savings to their occupational pension plans.

Had access to the pension application (and thus delivery of the invitation letters) been randomly assigned to part of the insured individuals within the two funds, with no information spillover to insureds that did not receive it, we could estimate this policy-relevant parameter by simply comparing the voluntary contribution choices of the two groups. In our setting, all insured individuals 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 assumption, we show that the two funds insure individuals with similar characteristics and pre-treatment contribution behavior (in Section 4), and conduct standard 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 saving) 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.

We estimate the (short-run) effect of providing individuals with the possibility to use the pension app also adopting a difference in differences 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.[20] Compared to the difference in differences strategy, the event study design has the advantage of tracing out the full (post-treatment) dynamic trajectory of the effects.

Interpretation and potential threats This research design allows to identify the intention-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 problematic 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 we do not have sources of exogenous variation within groups of insureds that were given the possibility to access the pension app in a given period (the invitation letters were sent to all individuals insured with a pension

[20]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.

fund), we cannot identify the average treatment effect of the pension app.[21]

However, we exploit the information about who self-selects into registering in the pension app to provide further suggestive evidence about its role for voluntary contributions, shedding light on the main mechanism underlying the behavioral response. We adopt the same event study design outlined above using only data for the insureds that will eventually register into using the pension app. Hence, 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 the behavior of "similar" (i.e., 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 people receiving the letter in 2017 signed up to the pension app after the end of the fiscal year.[22]

4 Data and Descriptive Evidence

We use administrative data provided directly by the two pension funds. We use data at the individual level for the years 2013 to 2019. The data include error-free information on annual labor income, mandatory contributions and end-of-year stock of pension wealth in the occupational pension plan, end-of-year buy-in potential and the total buy-ins made by each insured in the past. The data also include information on projected pension wealth and projected annuities under the current contribution scenario, as reported in the yearly communications made to the insureds. Further, the data include information on transactions (voluntary buy-ins) during the year. We have information on individual's gender, marital status, municipality of residence, sector of employment, level of employment (percentage), age, tenure in the firm as well as the time-varying conversion rate applied by the pension funds to the accumulated pension wealth at retirement. Finally, we can link the pension fund data with information about whether an individual is registered in the digital pension application in June 2019.

[21] 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 B1 in Appendix B.)

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

4.1 Sample characteristics

The sample consists of individuals that have not yet retired. Individuals drop out of the sample when they switch employers that insure individuals with another pension fund, when they stop working or when they retire. Individuals appear in the sample when they start working for one of the companies covered by the two pension funds. We restrict the sample to individuals between 25 and 65 years of age with annual earnings between 45'000 CHF (minimum wage for full time workers) and 250'000 CHF (99-percentile of the income distribution in Switzerland).

Table C1 in Appendix D reports a comparison of key statistics in our sample and in the Swiss labor force. Our sample is fairly representative of the national population of workers with respect to gender, age and labor income. Around 61% of insureds in the two pension funds are male, compared to around 59% in the active population. Insureds are around 42.4 years old in our sample, compared to 41.8 in the national statistics. Finally, median annual wage is only slightly lower in our sample (CHF 76'037) than in the Swiss labor force (CHF 78'024).

Table 1: Summary Statistics - by fund for year 2016

	Fund A	**Fund B**		**t-test**
	mean	mean	difference	test statistics
Age	42.378	42.631	0.253	(0.46)
Gender (male)	0.583	0.791	0.208***	(8.22)
Wage (log)	11.306	11.285	-0.0210	(-1.04)
Tenure in firm	4.606	4.539	-0.0667	(-0.24)
Projected replacement rate	0.243	0.250	0.00681	(1.37)
Potential buy-in (CHF)	76028.497	74877.874	-1150.6	(-0.21)
Buy-in (binary)	0.030	0.029	-0.00157	(-0.18)
Buy-in amount (log)	0.300	0.269	-0.0302	(-0.34)
Observations	2627	421	3048	

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.

Even though we are not in a controlled experimental setting, the credibility of our empirical strategy for estimating the effect of making the pension app available relies on whether individuals insured with fund B represent a good control group for the behavior of the individuals insured with fund A. Table 1 reports a comparison of selected figures in the two funds for the year 2016 (the year before the introduction of the pension app). Individuals insured with funds A and B are balanced with respect to age, tenure with the current employer, wage and accumulated pension wealth. Fund B insureds a larger share of men compared to fund A.

Importantly for our goal of estimating the effect of providing access to the pension app on voluntary contribution, individuals insured with the two pension funds have the same buy-in potential in the pre-treatment period. Further, they also show very similar contribution behaviors: both the share of insureds choosing to make an additional voluntary contribution to the occupational pension plan and the contributed amount are statistically equal between the two groups before the introduction of the pension app. We thus find that insureds with funds A and B are statistically balanced on most observables. However, because we do observe differences in the composition of the two groups with respect to gender, we control for the predetermined variables in Table 1 in our event study regression models to ensure conditional exogeneity in the timing of pension app roll-out.

4.2 Descriptive evidence

Before presenting the estimation results for the effect of providing access to the pension app, we wish to document key facts in the administrative data about: (i) the degree of retirement preparedness of older workers; (ii) the extent of the potential for tax-favoured voluntary savings; (iii) voluntary contribution decisions; (iv) the demand for digital retirement-related information. Empirical evidence on (i) and (ii) is particularly important to understand the potential role of providing pension-related information through the app for individuals' contribution decisions.

We first present some statistics from the data and then study the role of possible socio-demographic determinants in a regression framework. The latter also allows to study the life-cycle patterns of buy-in potential and contribution decisions. In fact, as well known, it is not possible to separate age, cohort and year effects without imposing some restrictions (see, e.g., Ameriks and Zeldes 2004). We describe below how we tackle this issue.

4.2.1 Retirement preparedness and tax-favoured saving potential

Heterogeneity in retirement preparedness How well are individuals insured with the two funds prepared for retirement? Answering this question may help gain insights into the importance of voluntary contributions for retirement preparedness and interventions that aim at promoting them.

The administrative data include information on the individual's projected pension annuities under the mandatory contribution scenario, as communicated to the insureds.[23] We

[23] This projection also includes past voluntary contributions.

focus on individuals older than 60 years of age and consider the ratio between projected annuity and current labor income as a measure of retirement preparedness.[24] On average, insureds above 60 in our sample will receive around 23.25% of their current income as occupational pension benefits.[25] Importantly, the data show a large heterogeneity in the projected annuity to income ratio, for a given income level (see Figure 4). This implies that, without additional voluntary contributions to the occupational plan, people will receive substantially different benefits after retirement, for a given level of earnings before retirement, reflecting a combination of different history of earnings and voluntary contributions.

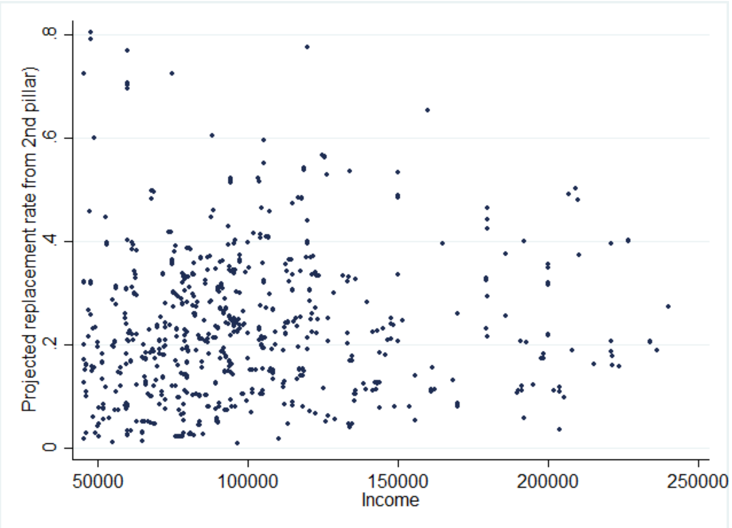


Figure 4: Projected replacement rate from second pillar

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.

To explore what explains heterogeneity in projected annuity to income ratio, we regress this measure of benefits adequacy on a second-order polynomial in individual's age, individual's gender, log wage, log number of years of tenure in the firm and marital status. We condition on year fixed effects to control for aggregate shocks. We report the OLS estimates of the regression coefficients in Column 1 of Table 2. The results show that male workers, higher income earners, and a longer tenure in a firm are associated with higher levels of projected annuity to income ratio. Overall, this descriptive evidence suggests the importance of

[24]This resembles the replacement rate at retirement, often used as an indicator for the adequacy of pension benefits. Our measure is clearly just a proxy for the actual replacement rate at retirement for individuals aged below 65.

[25]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% (data from Federal Statistical Office).

additional voluntary contributions for the retirement preparedness of (some) individuals in our sample.

Potential for tax-favoured retirement savings Do insureds have the possibility to buy-in and then increase their replacement rate at retirement from occupation pension benefits? The buy-in potential provides a measure of the amount of tax-favoured voluntary savings individuals can choose to allocate to the occupational pension plan. It thus also reflects the extent of fiscal benefits individuals are entitled to.

Figure **??** plots the individual buy-in potential to the occupational pension plan relative to individual's labor income, against individual's age. Two key facts emerge from the data. First, the potential buy-in to income ratio increases with individual's age, reflecting the fact that individuals do not entirely take-up the fiscal benefits arising from increasing wage profiles over the working lives or employment breaks.[26] The accumulated buy-in potential is substantial: close to retirement, individuals are entitled to buy-in (and then deduct from their personal income tax) almost twice their annual income on average. Second, there is large heterogeneity in potential buy-in to income ratio, for a given age. The dispersion of potential buy-in to income ratio also increases with individuals' age.[27]

As expected, we find that the buy-in potential to income ratio is negatively associated with the number of years of tenure in the firm (see Column 2 of Table 2). We do not find evidence of a gender gap in buy-in potential, nor a significant association between potential for tax-favoured voluntary contributions and income.

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:

$$\frac{TFP_{i,a,c,t}}{y_{i,a,c,t}} = \alpha + \beta_a \delta_a + \beta_c \psi_c + \beta_t \theta_t + \beta_0 t + \gamma X_{i,a,c,t} + \epsilon_{i,a,c,t} \tag{1}$$

where $TFP_{i,a,c,t}$ is the potential for tax-favoured voluntary savings, $y_{i,a,c,t}$ 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.(1). The estimated age profile of buy-in potential to income

[26]Figure C2 depicts the average income profile over individual's age in appendix C

[27]The standard deviation of potential buy-in to income ratio increases from around 0.198 between ages 25 and 35 to around 1.413 between ages 55 and 65. 9.46 % 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.

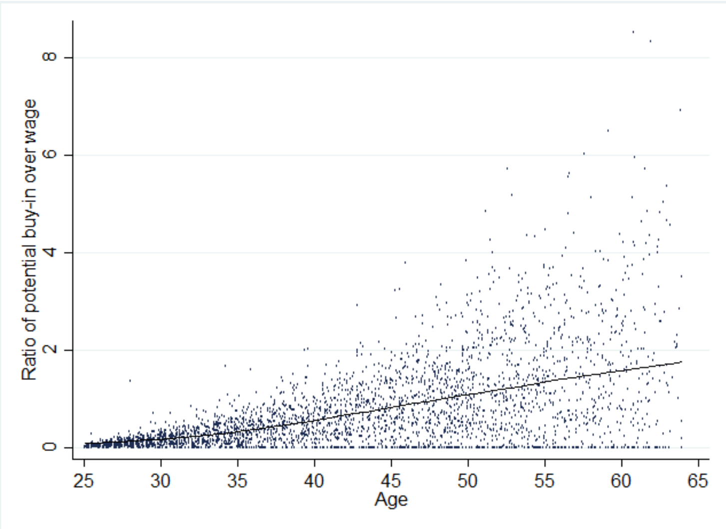


Figure 5: Potential buy-in to income ratio over age
Notes: The graph plots the scatter plot and local polynomial smoothing (black line) of the ratio of potential buy-in to wage over insureds' age for the pre-treatment year 2016. Data from two Swiss pension funds.

ratio is reported in Figure 6. The figure documents an increasing age pattern of buy-in potential over the working life, with individuals having the possibility to make tax-favoured contributions corresponding to twice their labor income when they approach retirement age.

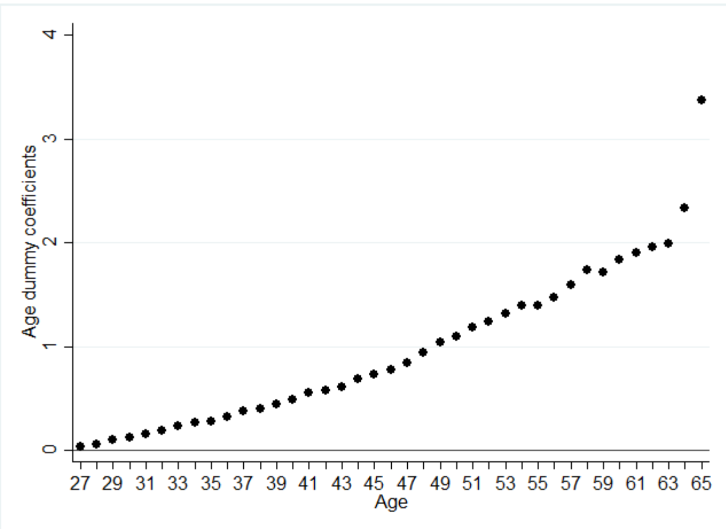


Figure 6: Estimated age-profile of potential buy-in to income ratio
Notes: The graph shows the coefficients of the age dummies of the regression model in eq. (1). Dependent variable is the ratio of the potential buy-in amount to the occupational pension fund over individuals' labour income. Data from two Swiss pension funds.

Besides the presence of limited knowledge about or inattention to pension rules and the fiscal incentives for voluntary contributions among insureds, there are other possible explanations for this evidence on untapped buy-in potential (see, e.g., Currie 2006 and Bhargava and Manoli 2015). In general, individuals may clearly find it optimal to allocate their savings to alternative investment options yielding higher returns. Notice, however, as described in Section 2, that the tax incentives guarantee a risk-free rate of return ranging between 10% and 40% (depending on the rank of the individual in the income distribution) on top of the guaranteed interest rate.[28] Further, individuals may find it optimal not to purchase additional retirement savings in the presence of liquidity or borrowing constraints. This barrier to the take-up of fiscal benefits should be especially important for low-income earners. However, the data do not seem to point towards liquidity or borrowing constraints as a prominent explanation for the limited take-up of fiscal benefits. Indeed, we observe substantial buy-in potential to income ratio also among high-income earners (see Figure C3 in Appendix C and the OLS estimates for the association between individuals' income and their buy-in potential to income ratio in Columns 2 and 3 of Table 2).[29]

4.2.2 Determinants of voluntary contributions

Who was taking advantage of the tax incentives for retirement savings before the introduction of the pension app?

Overall, 3.29% of the insureds use the buy-in option to increase their accumulated occupational pension wealth each year. Figure 7 plots the voluntary contribution rate by individual's age (panel a) and annual income (panel b). The data show a hump-shape age profile in the share of individuals making a voluntary contribution to their occupational pension plan over the working life, resembling well-known patterns in stock market participation (see, e.g., Fagereng et al. 2017 for Norway and Daminato and Pistaferri 2020 for the US). The contribution rate increases with age, ranging from around 1.5% among insureds younger than 40 years of age to peak at around 7% when individuals are aged 60.[30] Further, the share of insureds who make use of the buy-in option at least once before retirement is substantial. Figure C6 in Appendix C shows that while only about 10% of insureds made at least one buy-in by the age of 50, this share increases to nearly 40% by the normal retirement age.

As shown in panel (b) of Figure 7, the share of individuals choosing to make a buy-in

[28] Even considering the role of compound interest, alternative asset classes are then clearly dominated from an investment perspective at least towards the end of the individual's working life.

[29] In addition, Figure C5 shows substantial buy-in potential to income ratios also when restricting the sample to the three last years before retirement.

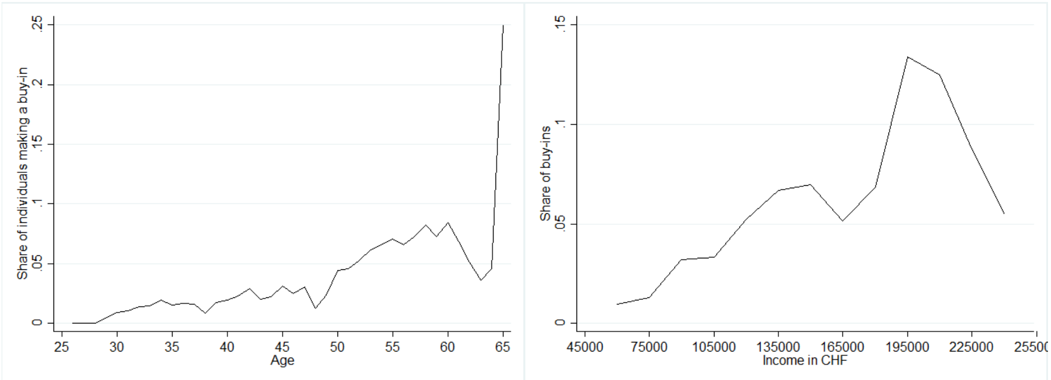
[30] We describe below how we separate age, cohort and year effects to estimate the life-cycle profile of voluntary contributions.

Table 2: Determinants of projected replacement rate, potential buy-in, voluntary contributions and demand for information

	Projected annuity	**Potential buy-in**		**Buy-in indicator**				**App registration indicator**	
	(1) OLS	(2) OLS	(3) OLS	(4) Probit	(5) LPM	(6) Probit	(7) LPM	(8) Probit	(9) LPM
Age	-0.00347**	-0.00584		0.00263	-0.00239			-0.0146	-0.0148
	(0.00163)	(0.0136)		(0.00213)	(0.00185)			(0.0108)	(0.0108)
Age (squared)	0.0000104	0.000697***		-0.00000787	0.0000471**			0.000141	0.000143
	(0.0000193)	(0.000168)		(0.0000229)	(0.0000227)			(0.000116)	(0.000117)
Wage (log)	0.0209***	-0.0262	0.00634	0.0469***	0.0568***	0.0509**	0.0575***	0.215***	0.223***
	(0.00558)	(0.0408)	(0.0426)	(0.00577)	(0.00779)	(0.0211)	(0.00794)	(0.0263)	(0.0283)
Gender (male)	0.0125***	0.0161	0.00270	-0.0149***	-0.0171***	-0.0134	-0.0152***	0.105***	0.102***
	(0.00349)	(0.0264)	(0.0274)	(0.00526)	(0.00552)	(0.00905)	(0.00561)	(0.0216)	(0.0212)
Tenure (log)	0.0217***	-0.163***	-0.144***	-0.00686***	-0.00676**	-0.00719*	-0.00720**	0.0434**	0.0433**
	(0.00201)	(0.0169)	(0.0185)	(0.00251)	(0.00269)	(0.00386)	(0.00303)	(0.0187)	(0.0188)
Constant	0.123*	0.192			-0.580***				-2.061***
	(0.0684)	(0.518)			(0.0952)				(0.391)
Marital Status FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Age FE	No	No	Yes	No	No	Yes	Yes	No	No
Cohort FE	No	No	Yes	No	No	Yes	Yes	No	No
Year FE	Yes	Yes	No	Yes	Yes	No	No	No	No
Time trend	No	No	Yes	No	No	Yes	Yes	No	No
Observations	16909	16909	15056	16782	16909	14149	15056	2052	2055

Notes: Estimates for descriptive models and for the age-profiles based on eq. 1 and 2. The table reports marginal effects from a Probit model in Columns (4), (6) and (8), and OLS estimates in Columns (1)-(3), (5), (7) and (9). 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)-(7): buy-in dummy indicating a positive yearly contribution (buy-in) to the occupational pension fund. Dependent variable in (8) and (9): registration status dummy indicating whether an individual was registered in the pension app mid 2019. Specifications (1), (2), (4), (5) 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. Specification (3), (6) and (7) 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 (8) and (9) 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. Significance levels are * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Data from two Swiss pension funds covering the years 2013–2019.

increases with their income up to 200'000 CHF and seems to slightly decline above this income level.



(a) By individual's age

(b) By individual's income

Figure 7: 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.

The contributed amounts corresponds to around 27.4% of the individuals' annual income when making a buy-in. The contributed amount to income ratio increases with individuals' age, ranging from around 16.3% for individuals between 25 and 35 years of age to almost 45.7% for individuals between 60-65 years of age (see figure C4 in Appendix C). These figures reflect the underlying age profile of buy-in option usage. Figure C4 plots the buy-in to income ratio conditional on non-zero buy-in in a given year. The data show that also the conditional buy-in to income ratio increases substantially over the individuals' working life. While individuals around 30 years of age contribute on average around 17% of their annual income when they decide to do so, individuals that are close to retirement make voluntary contributions amounting to nearly 40% of their annual income in their pension fund.

We study the role of possible determinants for the probability to make voluntary contributions in a regression framework. To estimate the life-cycle pattern of voluntary contribution, we adopt the same strategy described above for the investigation of the age profile of buy-in potential. That is, 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:

$$pr\left(P_{i,a,c,t} \mid z\right) = pr(\beta_a \delta_a + \beta_c \psi_c + \beta_t \theta_t + \beta_0 t + \gamma X_{i,a,c,t} + \epsilon_{i,a,c,t} > 0) \tag{2}$$

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.(1).

We again impose the restriction $\sum \beta_t = 0$ to eq.(2). 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.(2). We estimate eq.(2) using a probit and a linear probability model.

Columns (1) and (2) of Table 2 report the marginal effects from the probit model and the linear probability model, respectively, for the specification that parameterizes the age effects using a second-order polynomial. The estimated age-profile of voluntary contribution to the occupational pension plan obtained using the Deaton-Paxson restriction is plotted in Figure 8, with the full estimation results reported in Columns (3) and (4) for the probit and linear probability models, respectively. The figure shows a distinct hump-shaped age pattern of voluntary contribution between age 25 and age 64. The contribution rate increases with age, gradually up to age 45, and then more strongly, peaking when individuals are aged 60. After age 60, the contribution rate starts decreasing with age, to then spike in the year before retirement to around 23%. The estimation results also show that higher income earners are more likely to make a voluntary buy-in. Further, women are more likely to make a voluntary contribution to their occupational pension plan than men.

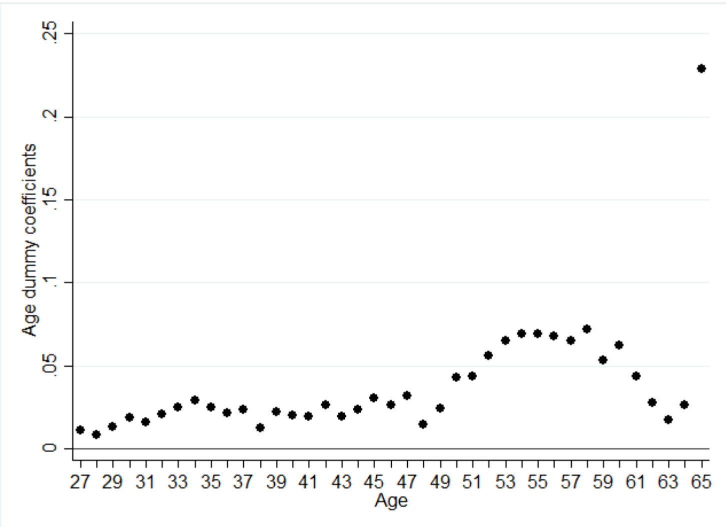
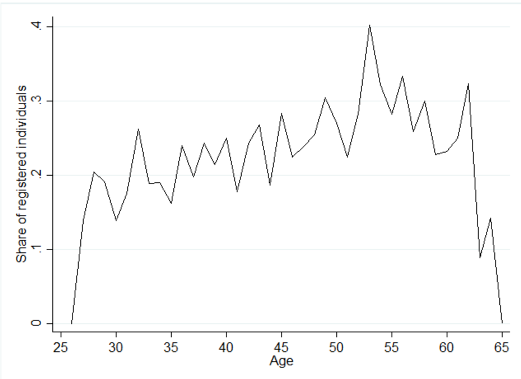


Figure 8: Estimated age-profile for the probability of making a voluntary contribution
Notes: The graph plots the coefficients of the age dummies of the regression model in eq. (2). Dependent variable is the dummy indicating whether an individual is making a voluntary contribution to her pension fund in a given year. Data from two Swiss pension funds.

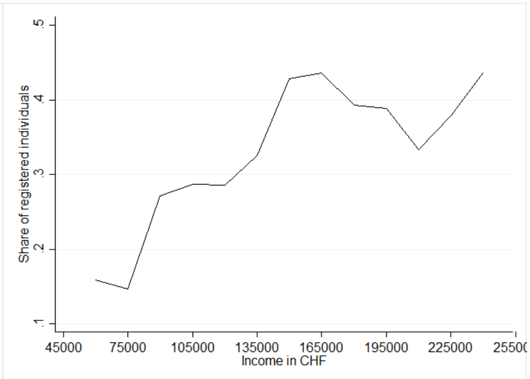
4.2.3 Determinants of demand for digital pension-related information

We now aim at describing the demand for digital pension-related information. As discussed in Section 2, we observe who had registered to the pension app in June 2019, but do not track registration behavior over time. Here, we then use end-of-year cross-sectional data for the year 2018.

Overall, 1'206 individuals from fund A (20.5 %) and 503 individuals from fund B (19.7 %) registered in the pension application by mid 2019. On average, insureds that registered to the pension app are one year older (46.9 years old) than individuals that never registered (45.9 years old). Figure 9, panel (a), shows a hump-shape age profile of registration rate. The share of registered individuals is increasing with age until the age of approximately 55, where it peaks at around 40% before it starts to decline until the retirement age. Another key fact emerging from the registration data is that higher income earners are more likely to register in the application, as shown in Figure 9, panel (b).[31]



(a) By individual's age



(b) By individual's income

Figure 9: 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.

To better characterise who chooses to access the pension app, we regress a dummy variable that takes the value of one for insureds that registered in the pension app, and zero otherwise, on the individual characteristics available in the administrative data. Columns 8 and 9 of Table 2 report the results of the probit and linear probability models, respectively. The regression analysis confirms that higher income is associated with a higher probability to register in the pension app. Further, men are around 10% more likely to register. Finally, longer tenure in the firm also positively correlates with the probability to register in the app. These results are in line with previous evidence about financial sophistication heterogeneity in the population (Lusardi and Mitchell, 2014). They then seem to point towards individuals

[31]Figure C7 in Appendix C reports the income distribution conditional on app registration status.

choosing to register in the app depending on their individual returns (in terms of tax-savings from voluntary contributions) they can obtain from accessing the enhanced pension-related information.[32]

5 Estimating the effect of making the pension app available

5.1 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:

$$y_{ift} = \alpha + \sum_{e=-4}^{2} \beta_e APT_{f(t+e)} + \gamma X_{ift} + \delta_f + \theta_t + \epsilon_{ift} \tag{3}$$

where y_{ift} is an indicator for the outcome of interest of individual i, insured with pension fund f in year t, $APT_{f(t+e)}$ ($e = -4, -3, .. + 2$, 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 ($e = -4, -3, .. + 2$) 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. 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

[32] Jappelli and Padula (2013) and Lusardi et al. (2017) proposed financial knowledge as a form of investment in human capital giving access to higher returns from financial wealth. They then hypothesize that individuals optimally choose the amount of investment in financial literacy depending on how much they can gain.

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. Standard errors are clustered at the individual level.

As discussed in Section 3, we estimate the short-run effect of making the app available also by restricting the sample to observations prior to the introduction of the pension app in fund B. In this case, we simply estimate the "static" specification of the difference in differences model:

$$y_{ift} = \alpha + \beta POST_{ft} * \delta_f + \gamma X_{ift} + \delta_f + \theta_t + \epsilon_{ift} \tag{4}$$

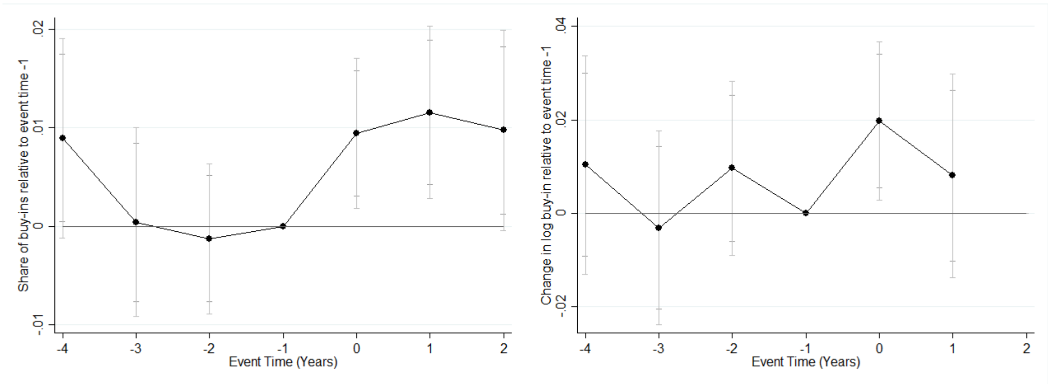
where $POST_{ft}$ is a time of intervention dummy taking value one in the period after fund A sent the invitation letter to register in the pension app, and all other variables are as in eq.(3).

5.2 Main results

To gain insights about the change in individual choices around the time of pension app introduction, we start estimating eq.(3) 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 (3) for the probability to make a voluntary contribution.

Panels (a) and (b) of Figure 10 report the marginal effects from a Probit model for fund A and fund B, respectively. The figures also reports 90 and 95 percent confidence intervals around the estimated effects. The estimation 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 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. The increase in contribution rates that follows the roll-out of the pension app seems to be persistent over time among individuals insured with fund A, while it becomes non significant in $e = 1$ among insureds of fund B. Overall, this evidence is confirmed when we use the log total contributed amount as dependent variable, as shown in Figure C1 in Appendix D.[33] 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.

[33] In this case, we estimate the model using OLS.



(a) Fund A

(b) Fund B

Figure 10: 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. (3) 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 2013-2019.

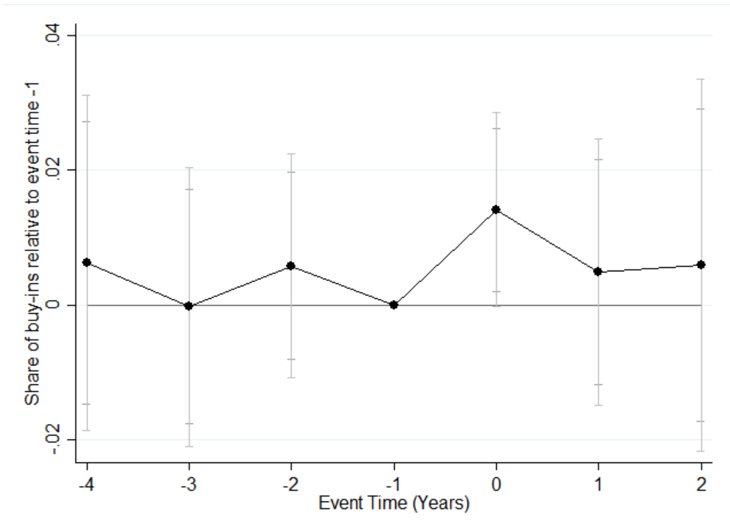


Figure 11: ITT: Event study coefficients for the probability to do a buy-in
Notes: The graph reports marginal effects of the event study coefficients from a Probit model based on the model in eq. (3). Dependent variable: buy-in dummy indicating a positive yearly contribution (buy-in) to the occupational 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 C2 in Appendix D. Data from two Swiss pension funds from 2013-2019.

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 (3). Figure 11 plots the impacts of the invitation letter to register in the app across event time.[34] 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.

Table 3: DID specifications for ITT effect of making app available on voluntary saving

	Buy-in indicator				**Contributed amount (log)**	
	Entire sample		Before 2018		Entire sample	Before 2018
	(1)	(2)	(3)	(4)	(5)	(6)
	Probit	LPM	Probit	LPM	OLS	OLS
Post*Fund	0.0180**	0.0145**	0.0154*	0.0137*	0.137**	0.124*
	(0.00848)	(0.00668)	(0.00881)	(0.00730)	(0.0643)	(0.0705)
Fund	-0.00311	-0.00119	-0.00220	- 0.000499	-0.00408	0.00963
	(0.00685)	(0.00683)	(0.00779)	(0.00701)	(0.0664)	(0.0676)
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes
Mean outcome in t - 1	0.0282	0.0282	0.0282	0.0282	.2795	.2795
Observations	15327	15450	11257	11342	15450	11342

Notes: Difference in differences estimates based on eq. 4. 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. Significance levels are * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. 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.

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,

[34] 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 C2 in Appendix D.

$e = 0$, the results show a jump in the probability to make a voluntary contribution. The effect fades away quickly over time, with non significant event study estimates for $e > 0$. We find a similar event time pattern when we estimate eq.(3) for the log of total contributed amount (see Table C2 and Figure C2) in Appendix.

To quantitatively assess the magnitude of this effect, we also estimate the difference in differences specification (4) on the full estimation sample as well as on the restricted sample before the year 2018.[35] The results show substantial intention-to-treat effects of providing access the the pension app. 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 (see Column 1 of Table 3). The estimation of the difference in differences model yields similar results (see Column 3). This is an economically large effect considering the average contribution rate of 2.82% in the pre-treatment period. Further, we find that the contributed amount increases by around 13.5 percent following the introduction of the pension app (see Column 5).

5.3 Behavioral mechanism

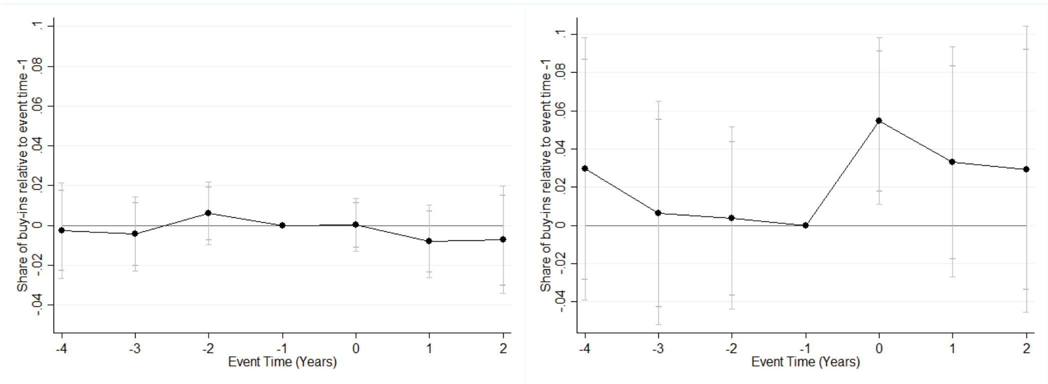
The event study estimates presented above should be interpreted as the intention-to-treat effect of providing access to the pension app. However, they are not informative about whether the behavioral response we find is driven by the actual usage of the pension app (and thus a reduction of information or transaction costs) or simply by an increase in the salience of retirement savings due to receiving the invitation letter. To provide suggestive evidence about which group of households changed retirement saving behavior following the invitation to access the pension app, we run our event study regression model (3) separately for individuals who eventually registered in the application and for those who never registered.[36]

On the left panel of Figure 12 are reported the event study estimates for the sample of insureds who never registered in the pension app, showing no impacts of the invitation letter, before or after the pension funds introduced the pension app.[37] In contrast, we find a large jump in the probability to make a voluntary contribution to the occupational pension

[35]The "static" specification of the event study design corresponds to the difference in differences specification (4). 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.

[36]As discussed in section 3, there is clearly self-selection into registering and using the application and we cannot make a causal claim about the effect of the pension app without additional sources of exogenous variation.

[37]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 C3 in appendix D.



(a) only never registered individuals (b) only registered individuals

Figure 12: Channel: 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. (3). 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 C3 in Appendix D. Data from two Swiss pension funds from 2013-2019.

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 12). The introduction of the pension app increases the probability to buy-in in this group of insureds by around 5.3 percentage points. Given the circumstance that the contribution rate among insureds that eventually register in the pension app is 6.6%, before its introduction, the estimated response is economically large. The estimation results of for the log of total contributed amount are plotted in figure C3 in appendix, and confirm a behavioral response only among insureds that register to the pension app. This group increases the contributed amount by almost 40% after receiving the invitation letter.

Together, these results provide compelling, though merely suggestive, evidence that the average intention-to-treat effect on contribution behavior is driven by those individuals who eventually register in the pension app. This result suggests that lack-of salience of retirement planning may not represent a major barrier to making voluntary contributions and taking-up the fiscal benefits individuals are entitled to, rather pointing towards the pension application reducing the information and transactions costs required to make informed retirement saving decisions.

5.4 Heterogeneous effects

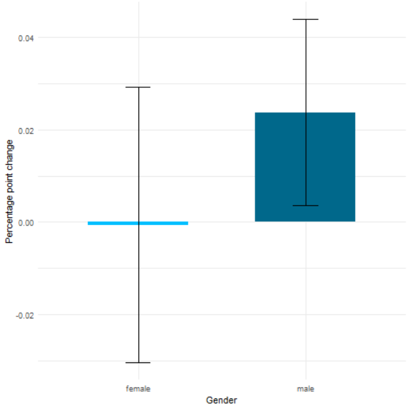
In this section, we investigate possible heterogeneity in the retirement savings response to the availability of the pension app. We consider effect heterogeneity along the dimensions: (i) gender, (ii) income and (iii) the buy-in potential relative to the wage.[38] We conduct the heterogeneity analysis both for the main event study design as well as conditioning on pension app registration status.[39]

Gender First, we estimate eq.(4) separately for men and women in the sample. As depicted in panel (a) of Figure 13, 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 2.37 percentage points among male sample members. Figure C4 in Appendix D also show that men increase the contributed amount by around 18.5 percent.

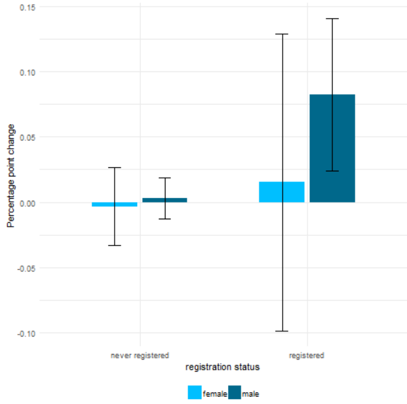
Splitting the sample further in individuals that self-select into using the pension app and individuals that never registered in the app allows us to provide additional suggestive evidence with respect to the behavioral channel. As shown in panel (b) of Figure 13, we find no treatment effect of sending 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 (8.08 percentage point increase in the probability to buy-in and 58.7 percent increase in the amount saved) but no significant response among women. Although the point estimates for the effect among registered female individuals are larger compared to that obtained using the sample of women who do not register, we do not find evidence of a significant response of women even conditional on accessing the pension app. A possible explanation for this evidence is that individuals' financial sophistication influences their ability to incorporate the information obtained through the 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).

[38] We do not find significant heterogeneity in the ITT effect with respect to age. Estimates for the effect heterogeneity with respect to age are reported in Table C4 in Appendix D.

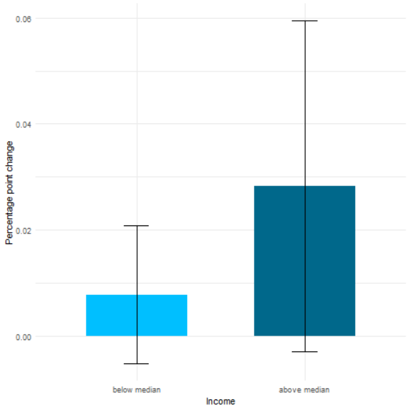
[39] The complete set of results is reported in Table C4 and Table C5 in Appendix D. We focus here on the results for the heterogeneous effects on the probability to make a voluntary contribution. Figure C4 in Appendix D reports point estimates and 95% confidence intervals for the heterogeneous effects on the log of contributed amount.



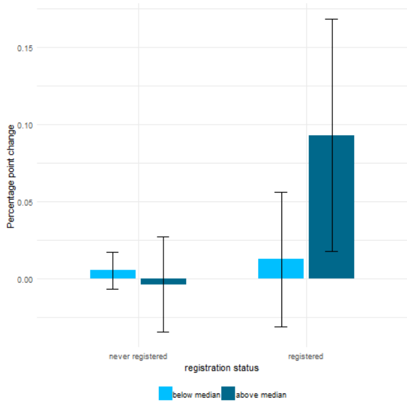
(a) gender



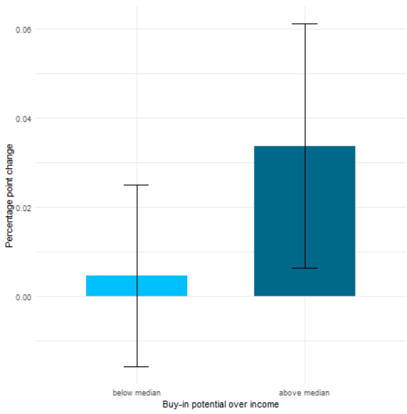
(b) gender & registration status



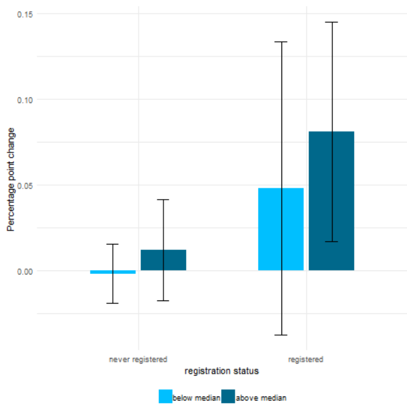
(c) income



(d) income & registration status



(e) buy-in potential



(f) buy-in potential & reg. status

Figure 13: Heterogeneity in intention-to-treat effect and behavioral channel

Notes: The graphs depict marginal effects of the difference in differences specification from a Probit model based on the model in eq. (4). 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 C4 and C5 in Appendix D report the estimates. Data from two Swiss pension funds from 2013-2019.

Income As discussed in Section 2, 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 (78'000 CHF).[40] As depicted in panel (c) of Figure 13, we find 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 2.83 percentage points following the introduction of the pension app, while the contributed amount increases by around 21.5 percent (see panel c of Figure C4 in Appendix D). In contrast, we do not find a significant contribution response among individuals with below-median income.

Regardless the income level, we again find no response to the intervention among individuals who do not register in the app (see panel d of Figure 13). Among individuals who do self-select into registering in the pension app, we find large contribution responses of individuals with above-median income, with the contribution rate increasing by around 9.30 percentage points, from a pre-intervention contribution rate of 8.28%. 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 saving 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.[41] 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. Our 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 3.37 percentage points following the introduction of the pension app, from a baseline contribution rate of 3.75%. We find no significant effect for individuals with a buy-in potential below the median (see panel (e) of Figure 13).

Also conditioning on the individuals' potential buy-in to wage ratio, we do not find an

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

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

effect of sending the invitation letters to register in the app among the individuals who never registered (see panel (f) of Figure 13). These results provide then additional evidence in support of the hypothesis that the introduction of the pension app induced a behavioral response through a reduction of information or transaction costs, and influenced the behavior of those individuals who, ex-ante, had more to gain from making a tax-favoured voluntary contribution.

6 Conclusion

This paper has presented quasi-experimental evidenceon the effects of providing individuals with the possibility to access enhanced, personalized, retirement-related information through a pension application on retirement savings.

We have documented that individuals insured with two Swiss occupational pension funds are entitled to substantial income tax benefits from voluntary retirement contributions that they only partially uptake, jointly with important heterogeneity in retirement preparedness. We have then shown that the invitation to access the pension app induced sizable voluntary retirement saving responses. Following the introduction of the pension app, the probability to make a tax-favoured contribution to the occupational pension plan, on top of the mandatory part, increases by around 1.8 percentage points, from an average contribution rate of 2.82% in the pre-treatment period. Further, we found that men, higher-income earners and individuals with higher potential of tax-favoured contributions exhibit larger saving responses.

Our results allow to gain additional insights about the mechanisms underlying the retirement saving response to an informational intervention. As discussed by Dolls et al. (2018), sending an information letter may increase the salience of retirement savings, and then induce a behavioral response, also in the absence of informational effects. Previous studies analysing the effect of information letter on retirement savings cannot then typically shed light on the relative importance of salience and informational effects. By showing no saving response among individuals that receive the invitation letter, but do not register in the pension app, our results suggest salience effects played a limited role in driving the observed saving response. Hence, our results show that limited knowledge about pension rules or the presence of transaction costs represent important barriers to informed retirement saving decisions.

We further show that the introduction of the pension app induced a substantial saving 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). Our results suggest that other factors such as limited knowledge about tax incentives or transaction costs represent important barriers to optimal retirement savings.

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, the "raw" information included in the pension app simply allows individuals to reduce the information and transaction costs needed to make more informed retirement saving decisions. The larger saving 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 retirement saving account, also points to the intervention being welfare-improving. Our results are especially important in light of the fact that 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.

Although we cannot isolate the effect of reducing the costs of information acquisition from that of reducing the direct transaction costs of making a retirement contribution, the finding that providing access to the pension app increases retirement savings remains policy relevant.[42] Our results prompt then policy makers concerned with improving individuals' savings for retirement to promote their introduction. However, to draw implications for the design of future policy interventions, we need a better understanding of the mechanisms underlying the saving response to the introduction of the pension app. Future research should then aim at isolating the effect of reducing costs of information acquisition from the direct transaction costs of making a voluntary contribution. Finally, future work might aim to explore how access to the pension app can be promoted as well as to estimate the effect of accessing the pension app on contributions to occupational pension plans, while isolating the effect of its different features.

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

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Appendix

A Informational intervention

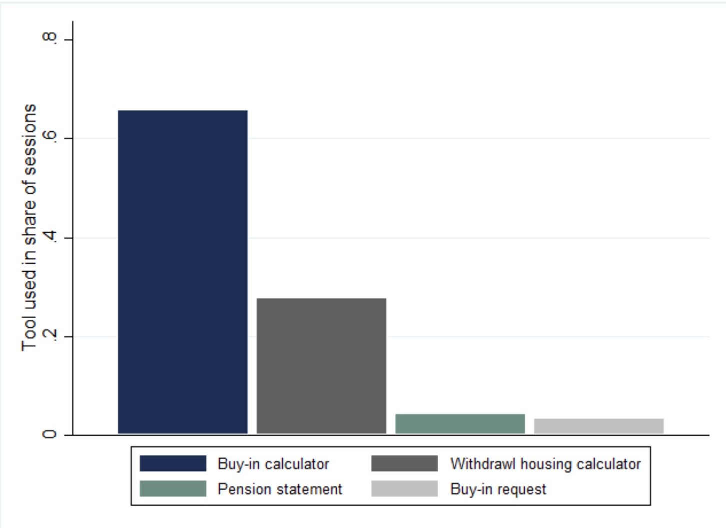


Figure A1: Usage of pension app

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:
E-Mail:

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.

B 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 B1 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 B1: First stage of possible IV approach

	Registration status indicator	
	(1)	(2)
	Probit	LPM
Fund indicator	-0.0277	-0.0284
	(0.0268)	(0.0280)
Age	-0.0134	-0.0136
	(0.0112)	(0.0113)
Age (squared)	0.000122	0.000124
	(0.000122)	(0.000122)
Wage (log)	0.230***	0.238***
	(0.0277)	(0.0299)
Tenure (log)	0.0485**	0.0482**
	(0.0199)	(0.0200)
Gender (male)	0.0991***	0.0962***
	(0.0230)	(0.0224)
Constant		-2.227***
		(0.412)
Marital status FE	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 indivdual was registered in the pensin 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. Significance levels are * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Data from two Swiss pension funds covering for the year 2019.

C Descriptive analysis

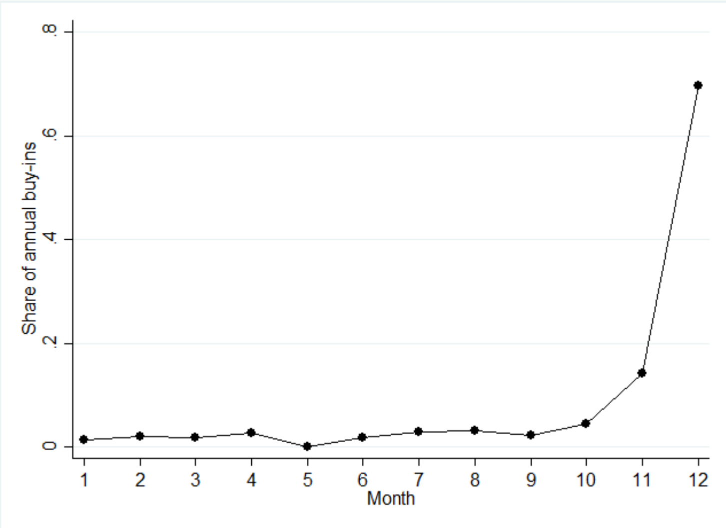


Figure C1: Timing of voluntary buy-ins.

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.

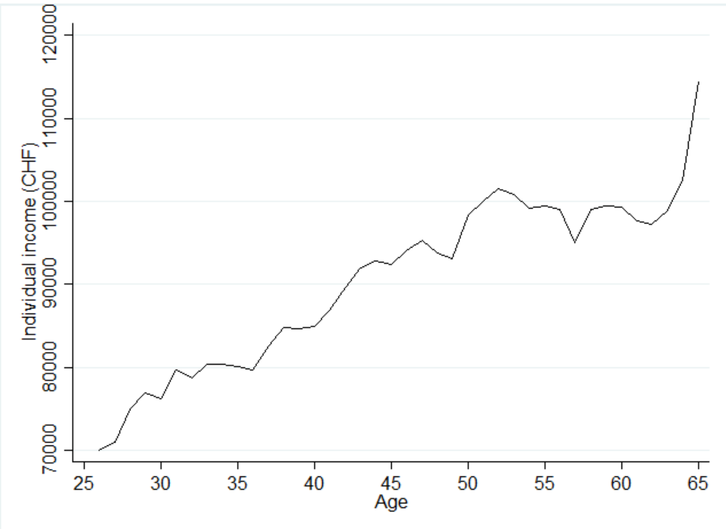
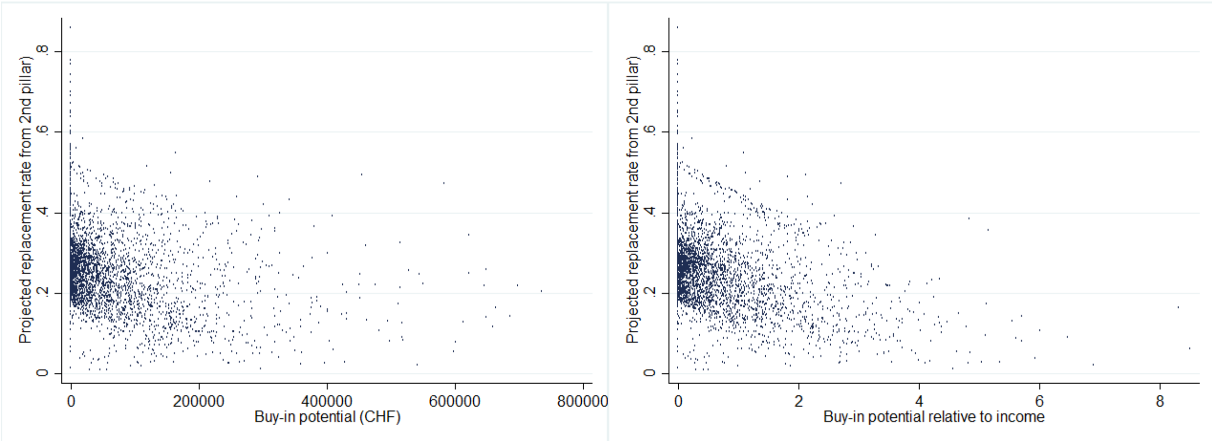


Figure C2: Income profile over age

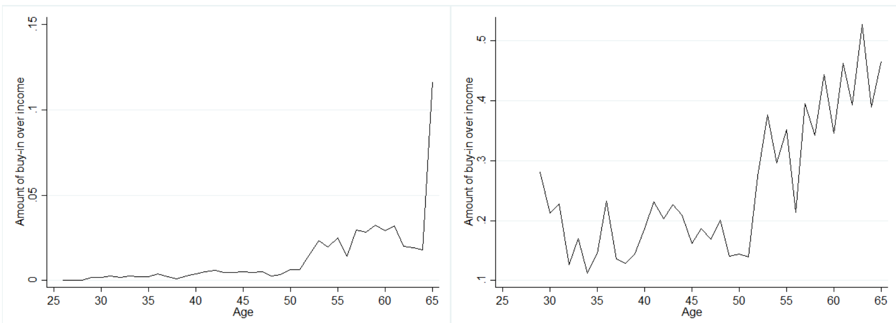
Notes: The graph depicts the income profile of individuals over age. The graph shows the average income for each year of age. Data from two Swiss pension funds.



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

Figure C3: 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.



(a) unconditional (b) conditional on making a buy-in

Figure C4: 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.

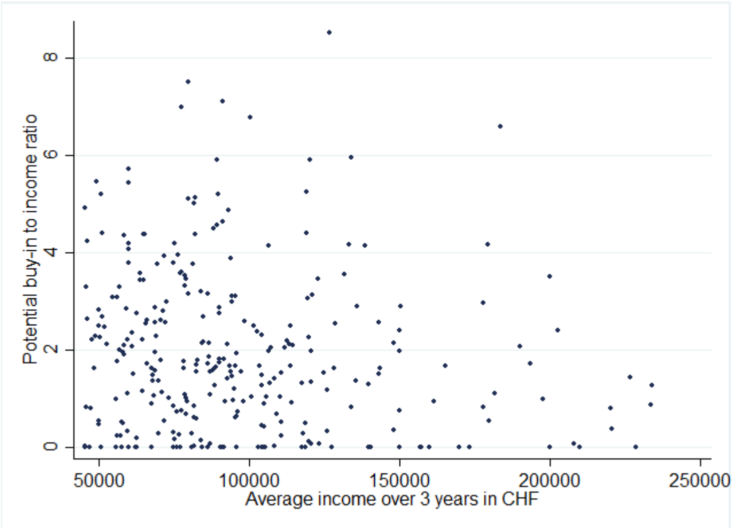


Figure C5: Potential buy-in to income ratio in last year before retirement
Notes: The graph depicts the ratio of the potential buy-in over individuals' last three years average labour income. The sample is restricted to the last three years before the legal retirement age. Data from two Swiss pension funds.

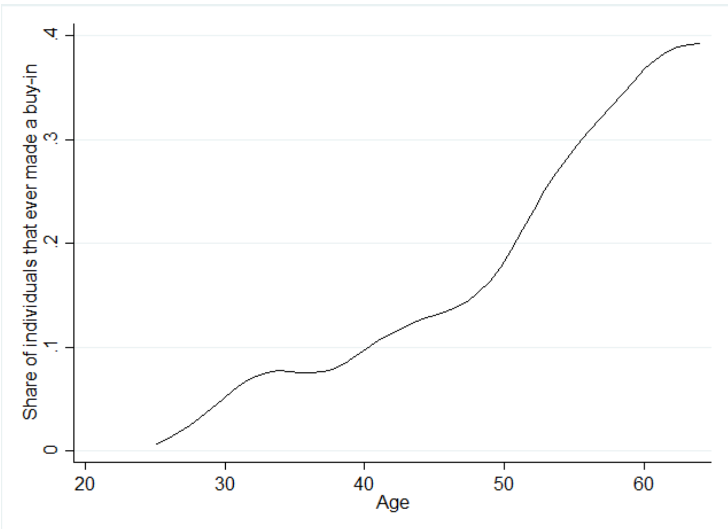


Figure C6: Share of people that has ever made a voluntary contribution by age
Notes: The graph depicts the local polynomial smoothing of the share of individuals that has ever done a voluntary contribution to her occupational pension fund. Data from two Swiss pension funds.

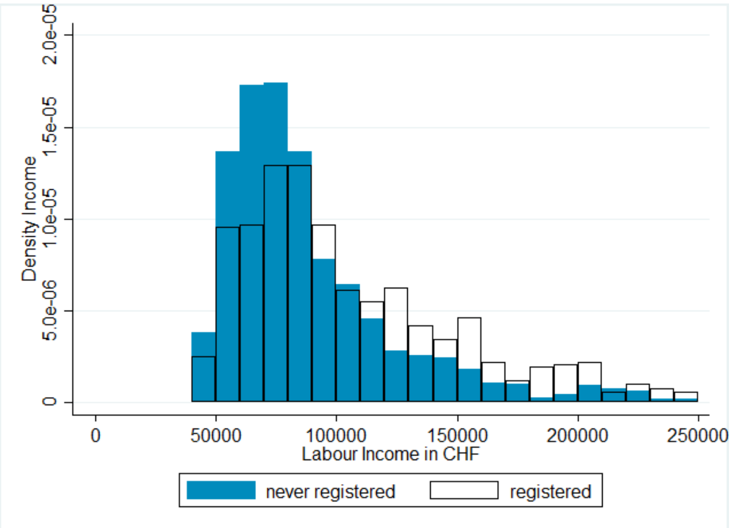


Figure C7: Histogram of income by app registration status

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.

D Statistics and estimates

Table C1: Summary Statistics - Comparison Sample and Switzerland

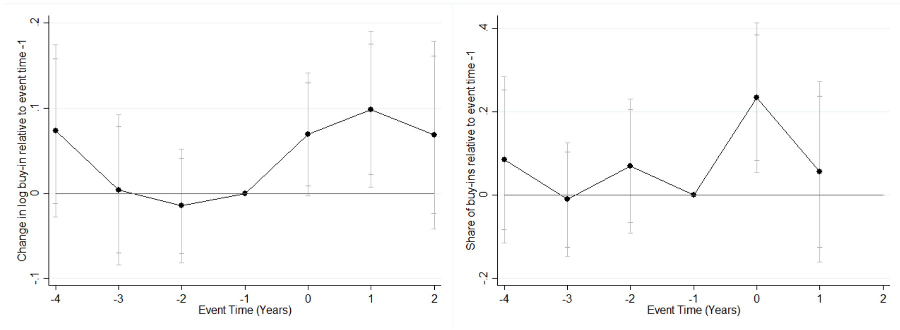
	Sample	**Switzerland**
Gender (male in %)	61.2	52.9 (in economic active population) 58.9 (new 2nd pillar recipients 2018)
Age (average)	42.41	41.8
Wage (median, CHF)	76'037	78'024

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.

Table C2: ITT: Effect of invitation letter and app availability on voluntary saving

	Buy-in indicator		**Contributed amount (log)**
	(1)	(2)	(3)
	Probit	LPM	OLS
eventtime -4	0.00527	0.00541	0.0397
	(0.0127)	(0.0113)	(0.109)
eventtime -3	0.000340	0.00192	0.0159
	(0.0106)	(0.00888)	(0.0862)
eventtime -2	0.00612	0.00417	0.0376
	(0.00847)	(0.00738)	(0.0706)
eventtime 0	0.0138*	0.0115**	0.106*
	(0.00736)	(0.00578)	(0.0557)
eventtime 1	0.00423	0.00150	-0.00319
	(0.0101)	(0.00961)	(0.0931)
eventtime 2	0.00494	0.00499	0.0271
	(0.0141)	(0.0133)	(0.130)
Year fixed effects	Yes	Yes	Yes
Control variables	Yes	Yes	Yes
Observations	15337	15460	15460

Notes: Event study 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). 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. Significance levels are * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Data from two Swiss pension funds covering the years 2013–2019. 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.



(a) Fund A (b) Fund B

Figure C1: 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. (3) 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 2013-2019.

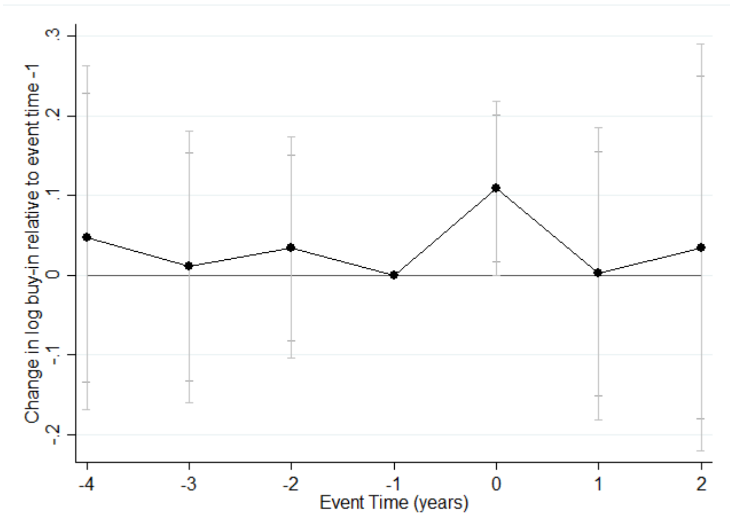


Figure C2: ITT: Event study coefficients (log buy-in amount)

Notes: The graph reports OLS coefficients of the event time dummies model based on the model in eq. (3). 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 C2 in Appendix D. Data from two Swiss pension funds from 2013-2019.

Table C3: Channel: invitation letter or pension app

	Buy-in indicator				Contributed amount (log)	
	Never registered		Registered		Never registered	Registered
	(1)	(2)	(3)	(4)	(5)	(6)
	Probit	LPM	Probit	LPM	OLS	OLS
eventtime -4	-0.0027	0.0002	0.0251	0.0221	-0.0222	0.2265
	(0.012)	(0.011)	(0.035)	(0.030)	(0.106)	(0.281)
eventtime -3	-0.0042	-0.0016	0.0093	0.0127	-0.0328	0.1554
	(0.009)	(0.009)	(0.030)	(0.023)	(0.084)	(0.221)
eventtime -2	0.0062	0.0042	0.0052	0.0040	0.0313	0.0510
	(0.008)	(0.008)	(0.024)	(0.018)	(0.072)	(0.178)
eventtime 0	0.0001	0.0000	0.0530**	0.0427***	-0.0051	0.4151***
	(0.007)	(0.006)	(0.022)	(0.015)	(0.056)	(0.143)
eventtime 1	-0.0082	-0.0076	0.0302	0.0210	-0.1014	0.2124
	(0.009)	(0.008)	(0.031)	(0.027)	(0.081)	(0.263)
eventtime 2	-0.0074	-0.0046	0.0248	0.0209	-0.0779	0.2022
	(0.014)	(0.013)	(0.038)	(0.034)	(0.128)	(0.325)
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Observations	11500	11632	3816	3828	11632	3828

Notes: Event study estimates based on eq. 3. 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. Significance levels are * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Data from two Swiss pension funds covering the years 2013–2019. 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 C4: Heterogeneity in intention-to-treat effect

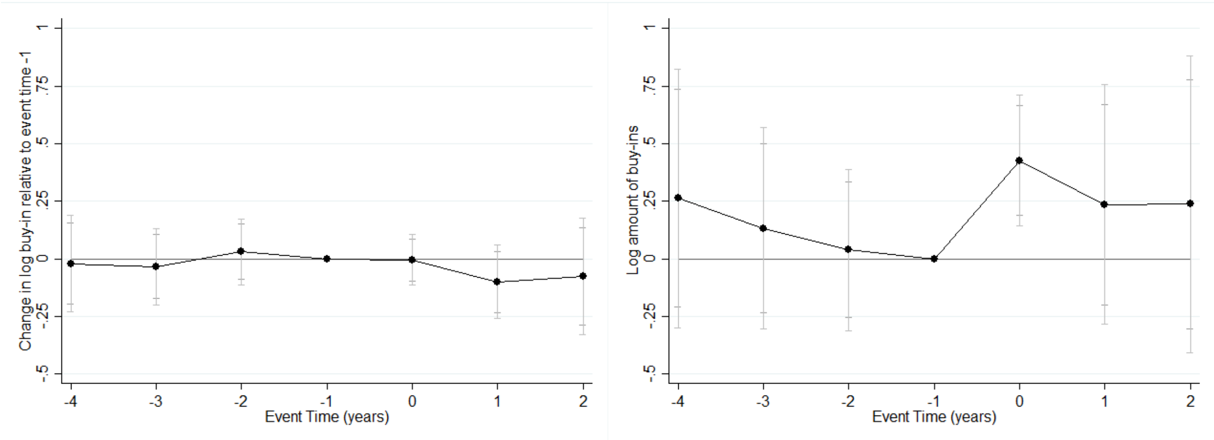
	Buy-in indicator		Contributed amount (log)	
	(1)	(2)	(3)	(4)
	Probit	Probit	OLS	OLS
(i) Gender	Female	Male	Female	Male
post	-0.000653	0.0237**	0.0141	0.185**
	(0.0152)	(0.0103)	(0.140)	(0.0741)
Year fixed effects	Yes	Yes	Yes	Yes
Control variables	Yes	Yes	Yes	Yes
Observations	5619	9687	5698	9762
(ii) Income	below median	above median	below median	above median
post	0.00780	0.0283*	0.0776	0.215*
	(0.00664)	(0.0159)	(0.0586)	(0.115)
Year fixed effects	Yes	Yes	Yes	Yes
Control variables	Yes	Yes	Yes	Yes
Observations	7517	7816	7592	7868
(iii) Buy-in potential over wage	below median	above median	below median	above median
post	0.00449	0.0337**	0.00616	0.265***
	(0.0104)	(0.0140)	(0.0944)	(0.0908)
Year fixed effects	Yes	Yes	Yes	Yes
Control variables	Yes	Yes	Yes	Yes
Observations	7694	7637	7729	7731
(iv) Age	below median	above median	below median	above median
post	0.0129	0.0152	0.0962	0.134
	(0.00927)	(0.0130)	(0.0703)	(0.109)
Year fixed effects	Yes	Yes	Yes	Yes
Control variables	Yes	Yes	Yes	Yes
Observations	8295	8241	8351	8337

Notes: Difference in differences estimates based on eq. 4. 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. Significance levels are * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. 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 C5: 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	-0.00344	0.00313	0.0153	0.0821^{***}	0.00143	0.0165	0.113	0.587^{***}
	(0.0152)	(0.00800)	(0.0581)	(0.0298)	(0.146)	(0.0699)	(0.489)	(0.182)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4589	6898	989	2780	4665	6967	1033	2795
(ii) Income	below median	above median	below median	above median	below median	above median	below median	above median
Post	0.00537	-0.00370	0.0126	0.0930^{**}	0.0642	-0.0559	0.0845	0.708^{***}
	(0.00618)	(0.0157)	(0.0223)	(0.0385)	(0.0614)	(0.124)	(0.186)	(0.228)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	6166	5313	1333	2482	6255	5377	1337	2491
(iii) Buy-in potential over wage	below median	above median	below median	above median	below median	above median	below median	above median
Post	-0.00174	0.0121	0.0479	0.0808^{**}	-0.0801	0.103	0.273	0.706^{***}
	(0.00884)	(0.0150)	(0.0435)	(0.0326)	(0.0997)	(0.0858)	(0.217)	(0.246)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5851	5637	1816	2000	5907	5725	1822	2006

Notes: Difference in differences estimates based on eq. 4. 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. Significance levels are * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. 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.

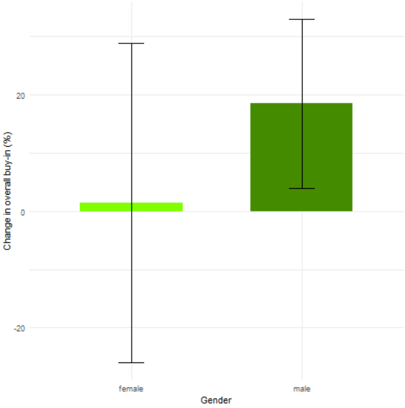


(a) never registered individuals

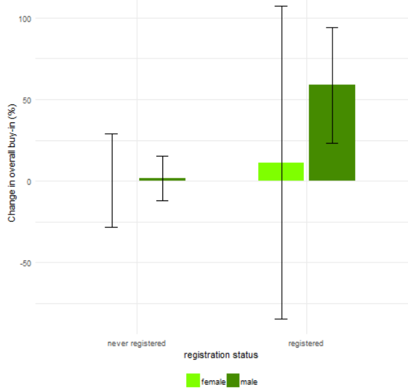
(b) registered individuals

Figure C3: Channel: Event study coefficients by registration status (log buy-in amount)

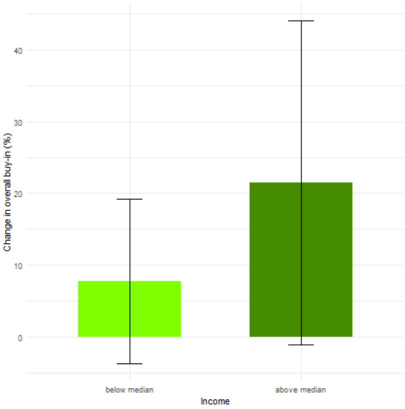
Notes: The graph reports OLS estimates of the event time dummies based on the model in eq. (3). Panel (a) shows the estimates for the restricted sample with individuals that never registered in then pension app and panel (b) shows the estimates for the restricted sample with only individuals that have 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 C3 in Appendix D. Data from two Swiss pension funds from 2013-2019.



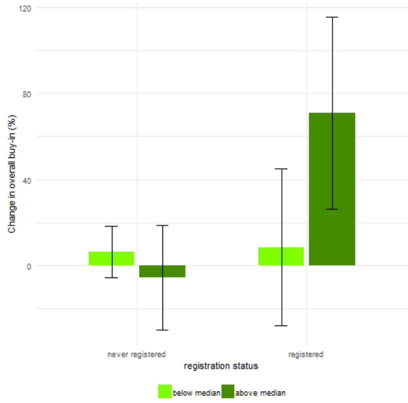
(a) gender



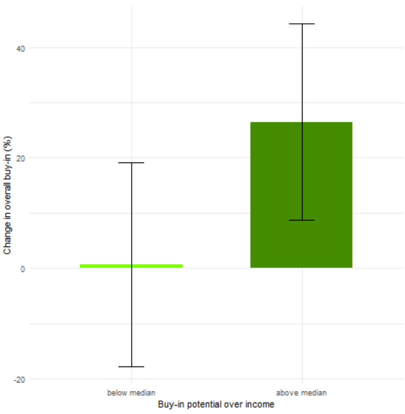
(b) gender & registration status



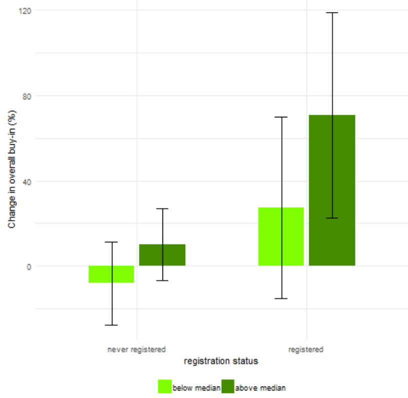
(c) income



(d) income & registration status



(e) buy-in potential



(f) buy-in potential & reg. status

Figure C4: 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. (4). 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 C4 and C5 in Appendix D report the estimates. Data from two Swiss pension funds from 2013-2019.

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