Learning About the Stock Market: Asset Allocation Spillovers from Defined Contribution Pension Plan Access*

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Abstract

This paper examines the impact of Defined Contribution (DC) pension plan enrollment on individuals' non-pension investment behavior. I address selection concerns by exploiting exogenous changes in Swedish occupational pension rules. Using Swedish Tax Registry data, I find that DC enrollment significantly boosts stock market entry probability, with an initial increase of 4% and a cumulative effect ranging from 9% to 63.5% over the first six years. This result is obtained after controlling for a variety of observables, including change in financial wealth. It thus highlights the importance of information costs for explaining the limited stock market participation observed in the data. For those individuals that were already stockholders, DC plan exposure raises the share of risky assets in their liquid portfolios, also consistent with a learning channel effect and/or DRRA preferences or tax optimization. Interestingly I find a mixed impact on diversification: while DC enrollment increases the likelihood of buying mutual funds and raises their share relative to financial wealth, individuals decrease their share of funds over risky assets. Overall, these findings show that DC plans positively impact stock market engagement outside retirement accounts by enhancing financial literacy, manifested in reduced stock market participation costs.

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1 Introduction

The rapid expansion of Defined Contribution (DC) pension plans worldwide, driven in part by the funding issues faced by traditional Defined Benefit (DB) plans, is one of the most profound transformations in retirement savings in the last decades. This change has transferred the responsibility of investment decisions from institutions to individuals, bringing millions into direct contact with financial markets. For a large number of households this is their very first exposure to equity investments since stock market participation rates outside retirement plans is limited.[1]

In this paper I study the impact of DC plan access on the investment behavior of individuals in their non-retirement accounts. This is a particularly important question given the expansion of DC pension plans worldwide, and its potential to re-shape household portfolio decisions. This is a difficult question to answer because DC plan participation is typically not randomly assigned, and thus may correlate with individual saving and investment preferences, potentially biasing the results. This concern has therefore limited previous research to provide descriptive and correlational evidence on this specific topic.[2]

I establish a causal relationship between DC plan exposure and changes in non-pension investment behavior by leveraging exogenous variations in DC enrollment rules across cohorts and time in Sweden between 2000 and 2007. Specifically, I exploit both the differences in the DC enrollment age rules between different occupations and staggered rule changes in Sweden's occupational pension system to isolate the causal effect of DC plan enrollment on investment behavior in non-retirement accounts. I find that DC plan access leads to an initial 4% increase in stock market entry decisions, with a cumulative rise between 9% to 63.5% over the next five years, consistent with a gradual learning process and inertia in household portfolio decisions. Furthermore, I show that exposure to DC plans also influences the risk-taking behavior of existing stockholders, who increase the risky share in their non-retirement accounts by 7.7 percentage points.[3] Collectively, these results highlight the potential of DC plans to shape broader financial behavior beyond retirement savings only.

The increase in stock market entry rates has important implications for theories of limited stock market

[1] Only 30% of the US population participate in the stock market through non-retirement accounts based on the 2022 Survey of Consumer Finances data. Furthermore, in the subsample of people without any retirement savings, stock market participation is only 8%. Guiso, Sapienza, and Zingales (2008), Christelis, Georgarakos, and Haliassos (2013) and Badarinza, Campbell, and Ramadorai (2016) document significantly lower numbers for most other countries.

[2] Weisbenner (2002), Karlsson et al. (2007), Dahlquist, Setty and Vestman (2018).

[3] As common practice in the literature, this is measured using the active change in risky share, to control for movements in asset prices and thus isolate pure rebalancing behavior.

participation. The existing literature has studied the role of participation costs (both monetary and informational) and first-order risk aversion in preferences for explaining the stock market participation puzzle.[4] First-order risk aversion would not predict a change in participation since households' preferences remain unchanged. Monetary participation costs (e.g. account fees) would also predict no effect once we control for changes in wealth, and a negative effect unconditionally, if households respond to the DC plan entry by reducing their non-retirement savings. Therefore, my results are strong evidence in support of informational participation costs, arising for example from limited financial literacy (Calvet, Campbell, and Sodini (2007), Van Rooij, Lusardi, and Alessie (2011)) or lack of trust in financial institutions (Guiso et al. (2008), Georgarakos and Pasini (2011)).

It is important to clarify that my results do not rule out first-order risk aversion or monetary participation costs as important factors contributing to limited stock market participation. They are just not potential explanations for my findings, which therefore highlight the role of informational costs and learning about stock market investments through the DC exposure. In fact, consistent with the importance of monetary participation costs as well, I find that the effect is much weaker once I do not control for changes in wealth, while further tests show that DC enrollment decreases private savings. This wealth effect implies a reduction in stock market entry by making those costs more relevant, and therefore counteracts the learning channel that I am isolating in the baseline regressions with all the controls.

I investigate this further by inspecting in more detail the changes in investments of previous stockholders. More precisely I study whether they are indeed moving to a more diversified portfolio as suggested by the learning channel. Here the result is mixed. On one hand, DC plan enrollment increases the probability of investing in mutual funds, and individuals do allocate a larger share of their financial wealth to mutual funds. However, the share of mutual funds as a fraction of risk asset holdings, stocks plus mutual funds, actually decreases. This suggests a potential (naive) substitution effect with investors viewing their mutual fund investments within DC plans as fulfilling their diversification needs. This nuanced finding highlights the complexity of investor behavior and the interplay between learning, preferences, and investment choices.

My identification exploits the specifics of occupational DC plans in Sweden. The occupational pension system in Sweden is as close as a national-wide and covers 90% of the workforce through four trade unions, covering different occupational groups. The enrollment to the DC plan is automatic once a person reaches the eligibility age.[5] Once enrolled in an occupational DC, employees get an individual account where they can make their own investment choices, with employer contributions of around 4.5% of income, depending on the collective agreement. A narrow group of union representatives decides on the pension collective agreements, so the changes in rules are exogenous to the preferences of individual employees. For instance,

[4] See Gomes, Haliassos, and Ramadorai (2021) for a survey of this literature.

[5] Hence, the setting avoids the selection issue of eligibility for a DC plan versus enrollment, the common barrier for the identification.

blue-collar workers experienced a drop in enrollment age from 28 to 22 in 2000, then down to 21 by 2002. For local government workers, the change happened in 2004 and decreased the enrollment age from 28 to 21. I further leverage these changes as a natural experiment to study how individuals, affected at different age and at different points in time, altered their investment behavior. Importantly, the enrollment to a DC plan is equivalent to the enrollment to the occupational pension for the first time for the particular subsample of cohorts studied in this research.[6]

To rigorously assess investment behavior, I focus on several key financial measures: stock market participation (whether an individual holds any stocks or equity funds outside of pension accounts), the change in risky asset allocation (the proportion of non-pension financial wealth invested in risky assets), and the active change in risky assets (which accounts for inertia and represents deliberate rebalancing decisions). To further examine asset composition, I consider diversification metrics, including the probability of buying equity funds (whether an individual's brokerage account shows new inflows toward new or existing funds compared to the previous year), the share of funds within risky asset holdings, and the share of funds in total financial wealth. These measures capture both the extensive and intensive margins of investment behavior, offering a comprehensive view of how exposure to equities through DC pension plans may influence individuals' non-pension investment decisions.

To approach the question, I use a dynamic difference-in-differences (DiD) approach, where the treatment indicator is enrollment in a DC account. This method takes advantage of the staggered introduction of DC plans across different sectors and age groups in Sweden. By comparing individuals who got a DC account to those who have not enrolled yet, I can isolate the effect of DC plan exposure on investment behavior. In contrast to the static DiD approach, which estimates the average treatment effect for the treated (ATT) by comparing the average change in outcomes experienced by the treated group to the average change in outcomes experienced by the control group, my dynamic specification utilizes a set of relative-time indicators, capturing the time periods leading up to the enrollment to a DC account (leads) and the second summation captures the time periods following treatment (lags). This allows me to track changes in investment behavior inside non-retirement accounts over time and understand both short- and long-term effects.

Additionally, it is important to consider that the control group might also be indirectly affected. Individuals who have not yet enrolled in a DC plan might be influenced through social networks and anticipation effects or even may have exposure to other (e.g. DB, public pension DC, or private) pension accounts. These spillover effects could lead the control group to exhibit changes similar to the treated group, thereby reducing the observed differences between them. Consequently, the estimated effect of DC plan exposure on investment behavior would be biased downward, suggesting that my findings likely represent conservative

[6]The only group in the sample who got the DC account after already having a DB pension is the central government employees aged 29 and older in 2000. These specifics are discussed in more details in Appendix A. This particular group is dropped at the sample selection stage described in Section 2.3.

estimates of the true impact.

The data for the analysis come from the Swedish Wealth and Tax Registry, a comprehensive dataset covering detailed information on finances, demographics, and employment for the whole population from 1999 to 2007. The sample selection criteria for this study include individuals aged between 18 and 34. This age range captures the variation in eligibility for the enrollment in a pension plan, and ensures that most individuals can be tracked back for at least 3 periods before and up to 7 years after treatment.[7] Furthermore, I apply several filters to ensure the robustness of the data. First, only those who are employed and have a positive labor income are included, focusing on economically active individuals. Second, the sample is restricted to those working within one of the four union group occupations, excluding military personnel. A financial wealth (FW) threshold is set, requiring individuals to have more than 1000 SEK (about 100 USD) in both the current and previous years to emphasize relevant financial activities. Additionally, individuals classified as dependents or "children" within family status are excluded to target independent financial behavior. Finally, only individuals who did not change their broad occupational group (one of the previous four categories) during the sample period and have complete occupational data are considered. The resulting dataset comprises around 3.62 million observations for approximately 769,000 unique individuals, covering the years from 1999 to 2007.

In my dataset I do not observe the actual investments in the DC account. This is not a direct concern since my object of study is the asset allocation decision in the non-retirement account. However, it will create some measurement error in the classification of treated individuals since some of them might not actually invest in equities in their DC accounts. Importantly this particular "fuzzy treatment" will only lead to a downward bias in my results since it is a one-sided mis-classification of non-treated as treated, but not the opposite.

I first estimate the dynamic treatment effects in a two-way fixed effects (TWFE) setting.[8] Recent work suggests that dynamic effect estimates from event-study estimators are problematic. Sun and Abraham (2021) show that, in the presence of staggered treatment timing and treatment effect heterogeneity, TWFE dynamic effect estimates for one relative-time period are contaminated by the causal effects of other relative-time periods in the estimation sample. I use the approach proposed by Callaway and Sant'Anna (2021) to correct the estimations for this potential bias.[9] I find that the results are robust to this alternative estimation

[7] To make sure all individuals in the sample can be observed for some time before the treatment, I filter out those who were older than 28 in year 1999, as this is their first year in a DC plan, and corresponds to the first available year in the data.

[8] In contrast to a 'standard' TWFE DiD estimation, where the fixed effects are unit and time-specific, I estimate the regression in differences and control for time and age fixed effects. This is important since there are life-cycle patterns inherent to the participation and risky share, and it is impossible to separately identify age, time and cohort effects in levels, since they are perfectly collinear. (Poterba and Samwick (1997), Ameriks and Zeldes (2004), Fagereng, Gottlieb, and Guiso (2017), Catherine (2022), Gomes and Smirnova (2022)).

[9] Both Sun and Abraham (2021) and Callaway and Sant'Anna (2021) suggest a robust solution, however, the latter is more preferable for my set-up as it gives more flexibility in settings without a never treated group, allow-

procedure.

Lastly, I accompany the result for Sweden with an analysis in the US. In this case, I focus on the change in the type of individual's retirement plan to DC, conditional on the fact they remained in the same job. The main empirical test aims to evaluate how the transition from a DB plan (or no pension plan) to a DC plan affects the likelihood of entering the stock market for non-participants, and the risky share for current stockholders. By analogy, I use a similar dynamic DiD setting, however, the variation comes from the staggered changes in the employer-specific pension rules. I estimate the model using the Health and Retirement Study (HRS) from 1994 to 2020. Naturally the identification is much weaker in this case, since I do not have exogenous variation. Therefore the results are prone to endogeneity and reverse causality, and furthermore the sample size is much smaller than in Sweden. Nevertheless I find similar evidence of positive effect of a DC account enrollment on stock market entry rates and the risky share of previous stockholders.

My research makes several important contributions. First, it provides strong evidence on the causal impact of DC plan exposure on non-retirement investments by using a natural experiment. The policy changes in Sweden that altered enrollment age for occupational DC plans provide a unique opportunity to study this effect without the usual biases. Second, the study explores whether DC plans can act as a form of financial education, increasing people's understanding and confidence in managing investments. It thus highlights the importance of financial literacy and learning for explaining investment decisions of households, and limited stock market participation in particular. Third, it contributes to discussions on retirement policy by showing how the design of pension plans can influence overall financial behavior.

This paper adds to the literature on portfolio choice in the presence of retirement accounts. The shift towards DC plans, where employees bear the investment risk, has led to significant research on how individuals manage their investments within these accounts, both empirically and theoretically (e.g., Madrian and Shea (2001), Choi, Laibson, Madrian, and Metrick (2002), Dammon, Spatt, and Zhang (2004), Gomes, Michaelides, and Polkovnichenko (2009)). Studies have also explored the impact of institutional settings on investment behavior, highlighting the significance of pension plan design and financial education (see Bernheim and Garrett (2003), Chetty, Friedman, Leth-Petersen, Nielsen, and Olsen (2014), Choukhmane (2019), Lindholm, Peters, and Sandström (2022)). However, these works do not fully address how DC plan exposure affects non-pension investments. Research examining the link between retirement plan design and the composition of savings indicates a positive relationship between the presence of DC plans and stock market participation (e.g., Weisbenner (2002), Karlsson, Massa, and Simonov (2007), Dahlquist, Setty, and Vestman (2018), Nielsson, Press, Rangvid, and Setty (2025)). Many of these studies, however, face challenges in establishing causal interpretations due to potential correlations with unobserved individual characteristics. There is also extensive literature on factors contributing to limited stock market participation, focusing on household preferences, participation costs, risks, and peer influences (e.g., Haliassos and Bertaut (1995),

ing the use of not-yet-treated observations instead.

Vissing-Jorgensen (2002), Guiso et al. (2008), Calvet et al. (2007), Gomes and Michaelides (2003), Duraj, Grunow, Haliassos, Laudenbach, and Siegel (2024)). This paper adds to this literature by emphasizing the importance of informational participation costs in stock market entry decisions and asset allocation.

In summary, despite the significant implications of DC plan expansion, there is a notable gap in empirical research on the causal relationship between DC plan exposure and non-pension investment behavior. This study addresses this gap by leveraging a natural experiment in Sweden, where policy changes created exogenous variation in DC plan enrollment.

The remainder of this paper is organized as follows. Section 2 describes the data, the institutional setting of the Swedish pension system and the policy changes that create the natural experiment. Section 3 discusses the empirical strategy, including the identification strategy and testable theoretical predictions. Section 4 presents the main findings, including the impact of DC plan exposure on stock market participation and portfolio risk composition. It also discusses the mechanisms underlying these effects. Section 5 provides a series of additional mechanism tests and robustness, while in Section 6 I replicate the analysis using the US data. Finally, Section 7 concludes the paper by summarizing the key contributions.

2 Data, Sample Selection and Institutional Setting

In this section, I provide a detailed description of the data sources, the sample selection process, and the institutional context relevant to my analysis.

2.1 Data

I use the tax registry data supplied by Statistics Sweden spanning eight years (1999-2007). The data covers the whole population in Sweden and provides detailed information on demographic characteristics, balance sheets, family links and more.[10] Since Swedish tax law prohibits joint filing, all tax returns are filed individually.

2.1.1 Demographics

Demographic information includes age, gender, marital status, education, and place of residence, as well as household composition and identification number. The household identification number allows us to group residents by living units and thus investigate finances at the family level.

[10] Applications of the same data include, but are not limited to Calvet et al. (2007), Calvet, Campbell, and Sodini (2009a), Calvet, Campbell, and Sodini (2009b), Girshina (2019), and Bach, Calvet, and Sodini (2020).

2.1.2 Occupation and Pension Scheme

Workers in the Sweden are enrolled in one of four main pension agreements depending on their occupation: blue-collar workers, white-collar workers, central government employees, and local government employees. These pension agreements are negotiated with the respective union confederations, which is why the occupational pension plans are standardized at this level of aggregation. I discuss this in more detail in the following subsection 2.2 on institutional setting and identification, and additionally in Appendix A.

Unfortunately, these agreements cannot be explicitly matched to individual workers or firms in my data. Instead, I proxy for this based on data on workers' occupations and industry codes. To determine whether individuals are in blue-collar or white-collar occupations, I use the 3-digit occupational code from the Standard for Swedish Classification of Occupations (SSYK). All occupations up to code 415 are considered blue-collar (including missing values), whereas codes above 415 are classified as white-collar. [11] Finally, there is an indicator for public sector workers, which distinguishes between local and central government employees.

2.1.3 Income

Income information is available both in total and by source of income. For capital income, the dataset provides, for each individual bank account or security, the income earned (such as interest and dividends) as well as all sales transactions, including the quantity and price of the securities sold throughout the year. However, the exact sale dates and details of asset purchases are not reported (since they are not taxed).

Labor income data includes gross labor income as well as information about the business sector. In addition, the dataset provides records of public and private pension income, military service compensation, and welfare transfers. Welfare transfers include unemployment benefits, workers' compensation, paternity and maternity allowances, student allowances, housing allowances, and disability support.

The sum of all income sources, including labor, capital, pensions, and welfare transfers, constitutes an individual's disposable income. This income reflects the total resources available for consumption, savings, and investment, accounting for all revenue streams reported in the dataset.

2.1.4 Wealth

To construct individual wealth, I utilize data from the Swedish Wealth Registry and tax records, which compile information from tax returns as well as financial institutions and banks. This dataset provides comprehensive details on all financial and real estate assets, as well as formal loans for every Swedish resident from 1999 to 2007, recorded annually on December 31.

[11] The detailed data on occupational code SSYK3 is available starting in 2001, so the information is backdated for the years 1999 and 2000. If an individual has a working status in all three years, they are assigned the same occupational code as in 2001.

Financial Wealth (FW_t) is defined as the total value of non-pension liquid assets. It includes both *risky assets* (such as mutual funds excluding money market funds, and directly held stocks)[12] and *risk-free assets* (such as money market funds and bank account balances). Stocks refer to direct holdings only, while risky mutual funds are classified into bond funds or equity funds. Equity funds broadly encompass any fund that invests partially in stocks, meaning balanced funds are counted as equity funds. Bank account balances are reported if interest earned exceeds 100 Swedish kronor (for the period from 1999 to 2005) or if the year-end balance surpasses 10,000 kronor (in 2006 and 2007). I impute unreported cash balances using the method developed by Calvet et al. (2007). Financial holdings other than bank accounts are constructed using information at the individual security level, identified by International Security Identification Number (ISIN), with pricing data sourced from FINBAS, Datastream, and Morningstar for Nordic stocks and mutual funds.

Real Estate Wealth (HW_t) includes both residential and commercial properties owned by individuals. The value assigned to real estate reflects its market value. For apartments, market values are based on actual transaction prices and adjusted by local price indices between transactions. For other real estate, Statistics Sweden estimates the market value using tax assessments, property characteristics, hedonic pricing models, and local price indices derived from transaction data.

On the liabilities side, I define *debt* (D_t) as the sum of outstanding student loans (termed as student debt) and other liabilities, including mortgages and other types of loans to financial institutions (collectively, non-student debt).

Liquid Wealth (LW_t) is defined as the sum of financial wealth and real estate wealth. *Total Wealth* (TW_t) is calculated as liquid wealth minus total debt. Throughout this paper, all values are reported in Swedish kronor (SEK) and adjusted for inflation to 2010 price levels.

A limitation of the data is that it lacks comprehensive information on pension wealth, since this is tax exempt. Specifically, I do not observe the complete details regarding state or occupational pension accounts, neither their current value nor the investment options within them. While some data is available on private pension contributions, I use proxies for PPM (premium pension) wealth and occupational pensions based on collective agreement rules.

2.1.5 Indicators of Stock Market Activity

Stock market participation is equal to 1 if the individual's risky financial assets have a positive value, and 0 otherwise. Stock market entrants are individuals who begin participating in the stock market, having

[12]The dataset also contains holdings of bonds, derivatives, and structured financial products; however, participation in these assets is low, and they form only a minor portion of household portfolios. The data also provides the total value of capital insurance products but does not specify their underlying asset allocation. Following Calvet et al. (2007) and Calvet et al. (2009a), these assets are excluded from the analysis for simplicity.

previously held no risky financial assets, while stock market exits refer to individuals who leave the market by reducing their risky asset holdings to zero.

I define *risky share* ω_{jt} as the value of risky asset holdings in individual's j's portfolio by the end of month t (A_{jt}) over the sum of her *risky* holdings and *riskless* holdings by the end of year t (C_{jt}):

$$\omega_{jt} = \frac{A_{jt}}{A_{jt} + C_{jt}}. \tag{1}$$

To obtain the value of equity holdings A_{jt}, I first calculate the value of the holdings in each particular asset i, then sum over all assets:

$$A_{jt} = \sum_i Q^i_{jt} P^i_t, \tag{2}$$

where Q is the number of shares and P is the share price. The change in the risky share $\Delta\omega_{jt}$ is then simply the difference between the current and previous period's risky share:

$$\Delta\omega_{jt} = \omega_{jt} - \omega_{jt-1}. \tag{3}$$

One potential issue with the change in the risky share, as defined in Equation (3), is that it may also reflect fluctuations in asset prices, potentially resulting in non-zero values even when no active rebalancing occurs. To separate the impact of an investor's deliberate rebalancing decisions from the effects of stock price changes,I adopt the approach used by Calvet et al. (2009a) and calculate the *active change in the risky share*.

I compute the value of asset holdings under the counterfactual that there were no trades between $t-1$ and t, labeled as A^p_{jt}:

$$A^p_{jt} = \sum_i Q^i_{jt-1} P^i_t. \tag{4}$$

Next, I compute the passive risky share—the risky share that we would have observed in the absence of any trades—as

$$\omega^p_{jt} = \frac{A^p_{jt}}{A^p_{jt} + C_{jt}}. \tag{5}$$

Finally, I can compute the active change in risky share from:

$$\omega^a_{jt} = \omega_{jt} - \omega^p_{jt}, \tag{6}$$

where ω_{jt} is risky share in the account j in year t.

To track how investors are distributing their capital to manage risk and achieve diversification, I calculate the *share of mutual funds*. This measure reflects the relative allocation of investments between mutual funds (or other diversified funds) and individual stocks.

To obtain this metric, I first compute the total value of assets in a particular class at the end of current year (period t) for every individual (j) in the sample (S_{jt} for direct stocks or with F_{jt} funds here and after):

$$\begin{aligned} S_{jt} &= \sum_i Q^i_{jt} P^i_t, \\ F_{jt} &= \sum_i Q^i_{jt} P^i_t. \end{aligned} \tag{7}$$

Next, I compute the share of funds over either risky funds or total wealth (including cash and cash-like holdings):

$$\begin{aligned} F^{\%Risky}_t &= \frac{F_{it}}{F_{it} + S_{it}}, \\ F^{\%FW}_t &= \frac{F_{it}}{FW_{it}}. \end{aligned} \tag{8}$$

Finally, I obtain the change of funds share between $t-1$ and t (conditional on equity holding in both periods):

$$\begin{aligned} \Delta F^{\%Risky}_t &= F^{\%Risky}_t - F^{\%Risky}_{t-1}, \\ \Delta F^{\%FW}_t &= F^{\%FW}_t - F^{\%FW}_{t-1}. \end{aligned} \tag{9}$$

2.2 Occupational Pension in Sweden and Identification Strategy

Sweden's pension system is composed of two main pillars: a universal public pension system[13] and a mandatory occupational pension system for workers whose employers participate in an occupational pension plan.

Occupational pensions are an important part of the pension system, accounting for an estimated 24% of total pension disbursements. Workers are covered by four central collective agreements between the confederations of unions on the Swedish labor market: two for the private sector (ITP for white-collar workers and Avtalspension SAF-LO for blue-collar workers), and two for the public sector (PA03 for central government workers and KAP-KL for local government workers).[14] Approximately 90% of the Swedish workforce is entitled to occupational pensions (Pensionsåldersutredningen, 2012).[15] This high and growing number is due to the fact that, firstly, almost every company in Sweden is part of one of the unions, and secondly, employees are enrolled in occupational pensions regardless of their contract terms and whether

[13] The total contribution rate for public pension is 18.5% of earnings, with 16% going to the notional account and 2.5% allocated to the The Premium Pension Scheme. See Palme and Svensson (2004), Sjögren Lindquist and Wadensjö (2006), Glans (2009), Lindquist and Wadensjö (2009), Anderson (2015) for additional institutional details.

[14] The approximate decomposition of occupational groups is as follows: white-collar workers comprised 23%, blue-collar workers 36%, local government employees 33%, and central government employees 9% of the total workforce covered by collective agreements in 2007.

[15] Self-employed individuals, entrepreneurs, and business owners are not covered by occupational pensions under collective agreements, and they must actively choose to save for retirement, often through pension insurance or other retirement savings options.

they are union members or not.[16] Contributions to occupational pensions are typically around 4.5% of an individual's income up to the income cap in the public pension system, with higher contribution rates applied to income that exceeds the cap. Importantly these contributions are made by the employer, not the employee, but they are placed into designated individual DC accounts. The individuals themselves then decide how to invest it across a pre-specified menu of investment funds.[17]

In my analysis I exploit both cross-sectional and time-series exogenous variation in enrollment in the DC plan. Cross-sectional variation arises because workers are only enrolled in the occupational DC plan once they reach a pre-determined age threshold, and this threshold varies across occupation groups. In addition, over my sample period there were changes in these age cutoffs, with a decrease in the DC enrollment age across all occupational groups. One reason for this decrease is the intended increase in the number of contribution accrual years to benefit employees. Although the direction of reform has been the same across sectors, the timing has differed. The timing of policy changes across occupations and cohorts provides exogenous variation in DC plan eligibility. Figure 1 shows the differences in eligibility ages for the different occupation groups over time.

[INSERT FIGURE 1 HERE]

To illustrate these differences and changes, consider the following cases. First, take two individuals of the same age but in different occupations. Person A is 25 years old in 2005 and works as a blue-collar worker. Person B is also 25 years old in 2005 but works as a white-collar worker. Following Figure 1, Person A, born in 1980, became eligible for the DC plan at age 22 in 2002 and has been enrolled for three years by 2005. On the other hand, the enrollment age for white-collar workers remained at 28 until 2007. It was only reduced to 25 in 2007 for those born in 1983 and later. Consequently, Person B, born in 1980, is not yet eligible for the DC plan in 2005 and will not be until turning 27 in 2007.

Similarly, consider two individuals in the same occupation and of the same age but from different cohorts. Person C is a local government worker aged 25 in 2003. Person D is a local government worker aged 25 in 2005. For local government workers, the enrollment eligibility age between 1998 and 2003 was at least 28 years old, and after 2004, the age was reduced to 21. Therefore, in 2003, Person C is not eligible for the DC plan at age 25 because the eligibility age is still 28. However, in 2005, Person D is eligible for the DC plan at age 25 since the eligibility age was reduced to 21 in 2004. Thus, although both are local government workers and of the same age, Person D benefits from the policy change and becomes eligible earlier than Person C did.

As these collective agreements are universal in the sense that they are equally applied to all workers within a given occupational group (and cover approximately 90% of workplaces), these exogenous changes

[16] Occupational schemes regulated by collective agreements also cover sickness, work-related injury, shortage of work, death, and parental leave.

[17] The same way as in 401(k) plan in the US.

across occupations and cohorts provide a natural experiment for identifying the impact of pension plan type on investments outside of the retirement account. In particular this avoids endogenous selection concerns arising from individual saving preferences and employer selection effects.

2.3 Sample Selection

The dataset is filtered according to the identification strategy, focusing on individuals aged between 18 and 34. This age range captures the variation in eligibility for the enrollment in a pension plan, and makes sure most of individuals can be tracked back for at least 1 period before and extending to up 7 years after treatment. To make sure all individuals in the sample can be observed for some time before the treatment, I further filter out those who where 28 or older in year 1999, as this was either their first year in a DC (or they will enter the sample as always treated) and the data starts at 1999. This will also help to factor out central government employees who were 29 and older in year 2000 as there was an additional policy change which gave rise to a DC component.[18]

Individuals classified as military personnel are dropped from the sample. Additionally, individuals with current and previous financial wealth below 1000 SEK (approximately 91 USD) are removed, as well as those classified as a "child" in the family status—meaning they are living with parents and potentially influenced by family decisions.

To focus on actively earning individuals, I retain only those with positive labor income, and further restrict the sample to those who are employed, and who work in one of the four occupations from union groups. Individuals who changed occupational groups during the sample period are also excluded to avoid contamination by different collective pension agreements.

Lastly, individuals with incomplete occupation information are removed to ensure data reliability. After these filters, I end up with approximately 3.62 million observations for 769,000 individuals between 1999 and 2007.

2.4 Descriptive Statistics

The descriptive statistics provide a comprehensive overview of the characteristics of the full sample included in the analysis and the subset of stock market participants in the study.

Panel (a) of Table 1 presents data for the full sample, which includes approximately 3.62 million observations. Most of individuals do not have children, and 21.6% are married. The most frequent education level is finished high school, with some individuals have some education post high school, but not a completed three-year general or vocational university program. Only quarter of the sample has completed three-year

[18] All the other three collective agreements had switched to a DC design much earlier (for the full or at least half of the contribution amount) as described in Appendix A.

general or vocational university program. Disposable income (Y) averages 176,565 SEK (16,036 USD), with substantial variation reflected in a standard deviation of 75,159 SEK. Just over half of the sample (53%) participates in the stock market, while entry and exit rates are relatively low, at 7% and 5%, respectively. Financial wealth (FW) has a mean value of 80,395 SEK and a large spread, as indicated by a standard deviation of 171,240 SEK. The average growth rate of financial wealth, measured by $\Delta FW/Y$, $\Delta \log FW$ and $\Delta_g FW$, is -0.05, 0.10 and 0.5, respectively.

Panel (b) of Table 1 describes some additional variables used in the analysis which are only available for stock market participants, namely, indicators for risky share and fund allocation, comprising around 1.69 million observations. The average risky share (w) in their portfolios is 0.43, and the mean change in risky share (Δw) is -0.02, while the active change in risky share (Δw^{active}) is 0.02. Participants allocate, on average, 76% of their risky investments to funds ($F^{\%Risky}$) and 32% of their total financial wealth to funds ($F^{\%FW}$). The probability of buying funds ($P(Buy_t^F)$) is relatively high, at 63%. The percentiles (25th, 50th, and 75th) highlight considerable variation in investment behavior and financial decisions among these participants.

[INSERT TABLE 1 HERE]

3 Empirical Approach and Testable Predictions

One of the challenges of identifying the causal effect of retirement account type on stock market activity outside such accounts is finding exogenous variation in the eligibility of individuals to participate in such plans. The "ideal experiment" would be to randomly assign DC plan to a sample of individuals. Differences in stock market activity could then be interpreted as the causal effect of changing the retirement plan type.

There is significant variation in 401(k) eligibility across households at any given time. Some of this variation, and consequently the differences in contributions, stems from factors that are likely beyond the individual's control. However, the eligibility for a plan might also be strongly correlated with personal preferences for saving, as noted by Bernheim (1997) Engen, Gale, Scholz, Bernheim, and Slemrod (1994). For instance, individuals who are inclined to save may seek out jobs that offer better pension options, or employers may introduce 401(k) plans in response to employee interest. So, most changes to 401(k) eligibility have either been universal or correlated with potential determinants of individual tastes for saving.

Empirically identifying the effect of pension plan type on stock market participation is challenging due to the potential influence of individual saving preferences on the choice of employers offering better pension plans, which is a common occurrence in the U.S. To address this endogeneity problem, one approach is to leverage exogenous variation in pension systems over time or across cohorts, resulting from policy changes. My empirical strategy exploits changes in collective pension agreements in Sweden that occurred between

2000 and 2007 summarized on Figure 1. For example, blue-collar workers experienced a drop in enrollment age from 28 to 22 in 2000, then down to 21 by 2002. For Local government workers the change happened in 2004 and decreased the enrollment age from 28 to 21. I leverage these changes as a natural experiment to study how individuals, affected at age and at different points in time, altered their investment behavior.

To assess investment behavior, I focus on key financial measures: stock market participation, the change in risky asset allocation or active change in risky share. I rely on a dynamic difference-in-differences (DiD) approach, where the treatment indicator is enrollment to a DC account. This method takes advantage of the staggered introduction of DC plans across different sectors and age groups in Sweden. By comparing people who got a DC account to those who have not enrolled yet, I can isolate the effect of DC plan exposure on investment behavior. In contrast to the static DiD approach, which estimates the average treatment effect for the treated (ATT) by comparing the average change in outcomes experienced by the treated group to the average change in outcomes experienced by the control group, my dynamic specification utilizes a set of relative-time indicators, capturing the time periods leading up to the enrollment to a DC account (leads) and the second summation captures the time periods following treatment (lags). This allows me to track changes in investment behavior inside non-retirement accounts over time and understand both short- and long-term effects.

I estimate the dynamic treatment effects in a two-way fixed effects (TWFE) setting. However, I deviate from the "canonical" TWFE DiD estimation, where the fixed effects are unit and time-specific, I estimate the regression in differences and control for time and age fixed effects. This approach is necessary because participation and risky share exhibit inherent life-cycle patterns, and it is impossible to separately identify age, time, and cohort effects in levels due to perfect collinearity (Poterba and Samwick (1997), Ameriks and Zeldes (2004), Fagereng et al. (2017), Catherine (2022)). By taking first differences of the data, I address the identification issue for participation and risky share, which also serves as an alternative to including fixed effects, effectively removing all time-invariant unobserved heterogeneity, such as individual preferences (Gomes and Smirnova (2022)).

3.1 Stock market participation

Equation 10 establishes the empirical setting to estimate the probability of entering the stock market for people with different DC enrollment status:

$$P(Entry_{it}) = \alpha + \sum_{j=-3}^{-1} \beta_j I[_{\tau^{DC}=j}] + \beta_1 I[_{\tau^{DC}=1}] + \sum_{j=2}^{6} \beta_j I[_{\tau^{DC}=j}] + \\ + \theta X_{it} + I[a_{it}] + I[y_t] + \varepsilon_{it} \quad (10)$$

$Entry_{it}$ represents whether individual i enters the stock market at time t, this means that the individual did not participate in the stock market before ($Partic_{t-1,t} = 0$). $\hat{\tau}^{DC}$ denotes years before/after getting DC (age_{it} - $age_t^{rule} + 1$). Indicator $I[\hat{\tau}^{DC} = j]$ equals 1 if $\hat{\tau}^{DC} = j$ is true. The main parameters of interest, the β_j's, are interpreted as the difference between the differences in probability to enter the stock market at time t between treated and untreated observations $\hat{\tau}^{DC}$ periods from treatment relative to the stock market entry probability differences between treated and untreated observations in the excluded periods. X_{it} is a vector of time-varying characteristics that are not perfectly correlated across individuals. $I[a_{it}]$ is a set of age dummies. $I[y_t]$ represents time fixed effects to account for any temporal factors that could influence stock market entries over the period. ε_{it} is a (regression) residual.

3.2 Risky share

Consider change in risky share (Eq. 3) for stock market participants ($Partic_{it} = 1$ and $Partic_{it-1} = 1$). In addition to the general change in risky share, I also analyze the active change in risky share to take into account inertia in rebalancing decisions. This approach helps isolate the effects of conscious decision-making by distinguishing active rebalancing from passive changes resulting from market fluctuations (as defined in Eq. 4 to 6). The (active) change in risky share of an individual's portfolio refers to how the proportion of financial assets allocated to risky investments (such as stocks) changes over time. The empirical model helps assess whether the introduction of a DC plan affects an individual's willingness to hold risky assets relative to safer assets. This analysis is important because DC plans typically offer equity exposure, and the study aims to understand whether this exposure influences how individuals manage risk in their overall portfolio.

The empirical models are:

$$\Delta\omega_{it}^{(a)} = \alpha + \sum_{j=-3}^{-1} \beta_j I[_{\hat{\tau}^{DC}=j}] + \beta_1 I[_{\hat{\tau}^{DC}=1}] + \sum_{j=2}^{6} \beta_j I[_{\hat{\tau}^{DC}=j}] + \\ + \theta X_{it} + I[a_{it}] + I[y_t] + \varepsilon_{it} \quad (11)$$

Here, $\Delta\omega_{it}^{(a)}$ represents the (active) change in risky share of individual i's portfolio between time $t-1$ and t. $\hat{\tau}^{DC}$ denotes years before/after getting DC (age_{it} - $age_t^{rule} + 1$). Indicator $I[\hat{\tau}^{DC} = j]$ equals 1 if $\hat{\tau}^{DC} = j$ is true. The main parameters of interest, the β_j's, are interpreted as the difference between the differences in changes in risky share between treated and untreated observations $\hat{\tau}^{DC}$ periods from treatment relative to the change is risky share differences between treated and untreated observations in the excluded periods. X_{it} is vector of time-varying characteristics that are not perfectly correlated across individuals. $I[a_{it}]$ is set of age dummies. $I[y_t]$ represents time fixed effects to account for any temporal factors that could influence change in risky share over the period. ε_{it} is a (regression) residual.

3.3 Testable Predictions

In this section I describe the specific mechanisms that I will be considering when testing the asset allocation response of non-retirement investments to the DC enrollment event.

3.3.1 Participation Decision

There is a long literature in household finance studying, both theoretically and empirically, the determinants of limited stock market participation.

One of the leading explanations is that households do not invest in stocks because they face participation costs.[19] These can be explicit monetary costs (such as brokerage fees), opportunity cost of time (e.g. monitoring the stock market, filling more complicated tax forms) or lack of information about how to invest in the stock market or the potential benefits of doing so. Related to the last point, it has been argued and shown empirically that stock market participation is negatively influenced by lack of trust in financial markets (see Guiso et al. (2008) and Giannetti and Wang (2016)) or limited financial literacy (Calvet et al. (2007) and Van Rooij et al. (2011)), and increases with education (Black, Devereux, Lundborg, and Majlesi (2018)) and IQ (Grinblatt, Keloharju, and Linnainmaa (2011)).

Enrolling in the DC account does not change monetary participation costs (hereafter MPC) in non-retirement accounts. Therefore, all else equal, the MPC channel would predict *a zero effect*. To the extent that individuals might decrease their private savings in response to the positive wealth shock from being enrolled in the DC account, that would lead to *a negative effect* from the MPC channel, as long as we do not control for wealth changes.[20]

By contrast, informational-driven participation costs (hereafter IPC) would predict *an increase* in stock market participation, as individuals learn about the stock market, and increase their financial education and their trust in the financial system.

Another leading explanation for limited stock market participation is preference-based, namely that households have preferences with first-order risk aversion.[21] However, this channel (hereafter referred to as the *preference channel*) would predict *a zero effect* in this context since investor preferences remain unchanged.[22] Similarly, theories of non-participation based on the correlation between labor income and

[19] See, for example., Vissing-Jorgensen (2002), Haliassos and Michaelides (2003), Gomes and Michaelides (2005), Bonaparte and Kumar (2018), Gomes and Smirnova (2022), Choukmane and DeSilva (2023).

[20] As individuals have less financial wealth they are less likely to find it optimal to pay a given participation cost.

[21] See, for example, Ang, Bekaert, and Liu (2005), Cao, Wang, and Zhang (2005), Gomes (2005), Barberis, Huang, and Thaler (2006), Chapman and Polkovnichenko (2009), Campanale (2011), Dimmock, Kouwenberg, Mitchell, and Peijnenburg (2016), Pagel (2018), Peijnenburg (2018), and Calvet, Celerier, Sodini, and Vallee (2023b).

[22] One could argue that the endowment of DC wealth equivalent to 4.5% of salary could introduce a background risk effect, potentially increasing risk aversion (Viceira (2001)). However, although the individual cannot choose the contributions to the DC account, she decides how to invest them. She can potentially choose a fully riskless investment, in which case there is no additional risk, hence the background risk interpretation is not straightforward.

stock returns (e.g., Benzoni, Collin-Dufresne, and Goldstein (2007) and Catherine (2022)) would also predict no effect, as that correlation remains unchanged.

3.3.2 Asset Allocation of Previous Stockholders

For those individuals that were already stockholders before, the learning channel would predict *an increase* in their risky share as they gain a better understanding of the benefits of investing and diversification, and increased trust in financial markets can also enhance their expected return on stocks.

Another important mechanism is tax optimization, since wealth accumulation in the DC account is tax free. Dammon et al. (2004) argue that investors are better off holding tax-efficient equity investments in the taxable account, and holding taxable bonds in the tax-deferred account. The tax optimization channel would, therefore, also suggests *a positive effect* on risky share.

Finally, if households have decreasing relative risk aversion (hereafter DRRA) then their optimal risky share will increase (decrease) as their wealth also increases (decreases). In this context the effect on risky share allocation will then depend on whether individuals evaluate their risk aversion relative to their total wealth or, due potentially to mental accounting, they consider their non-retirement wealth only. The former would predict a positive effect while the latter could lead to a reduction in the risky share if individuals save less in their liquid account.

4 Results

In this section, I present the empirical findings on the impact of DC pension plan enrollment on individuals' non-retirement investment behavior. The analysis focuses on two key aspects: stock market participation and portfolio allocation decisions. Specifically, I examine how exposure to DC plans influences the probability of entering the stock market for non-participants and affects the risky share of portfolios for existing stockholders.

4.1 Participation

The regression estimates of Equation 10 are presented in Table 2 with different sets of controls, progressively adding covariates such as occupation, education, marital status, and ownership status to investigate the robustness of the effect of DC plan exposure on stock market entry. The table shows the marginal effects evaluated at sample averages.[23] In the table, I only report the treatment effect in the first year of treatment

In addition, if anything, this additional channel would predict a negative effect on both stock market participation and the risky share, while in my results I find the opposite.

[23] Some of the coefficients are omitted in the Table 2 in order to facilitate the presentation, but they are all available upon request.

(coefficient β_1), while Figure 4 shows the full profile of DC enrollment effects on stock market entry over time.

[INSERT TABLE 2 and FIGURE 4 HERE]

In the baseline specification, I cluster standard errors at the individual level; however, the result is still statistically significant if I cluster at a more conservative age-year-region-occupation level instead.[24]

Effect on first year of treatment

The results in Table 2 highlight the impact of DC plan enrollment on stock market entry in "the first year" of treatment. The key variable $\hat{\tau}^{DC} = 1$ shows a highly statistically significant positive effect across all specifications. Specifically, the coefficient for $\hat{\tau}^{DC} = 1$ is 0.002 and statistically significant in the model without additional covariates, and increases to 0.003 with the addition of further controls in columns (2) added family status variables, and (3) added region fixed effects. These results indicate that individuals with access to DC plans are more likely to enter the stock market compared to those without access, suggesting a positive effect of DC plan exposure on stock market participation. In the sample, the average unconditional probability to enter the stock market for non-participants in the next year is 7.01%, which means that the obtained coefficient of 0.0028 translates to a 3.9% increase in stock market entry probability in the "first year" of DC plan enrollment.

Importantly, since the exact date of birth is not observed in my data, this is the effect on the first year of treatment, not after 1 year of treatment. Hence, while $\hat{\tau}^{DC}$ equals one year, the real τ^{DC} might be (way) less than this. In the extreme case, it could be just one day with a DC account, if the birthday falls on 31 December.

The variable $\Delta \log FW_t$, representing changes in financial wealth, shows a positive and highly significant effect in all models, implying that individuals with greater financial wealth are more likely to enter the stock market. This particular result is consistent with several previous studies on the determinants of stock market participation decisions and the role of monetary participation costs.

The positive and significant coefficient for log income $\log Y_t$ suggests that higher-income individuals are more likely to enter the stock market.[25]

Across the four broad occupation groups, individuals in central government, local government, and blue-collar occupations show significantly lower stock market participation rates compared to white-collar workers. Educational attainment also significantly influences stock market entry. The base/omitted category is no high school and I observe statistically significant positive and monotonically increasing coefficients up to

[24] Reported in Table A1 in Appendix C.1.

[25] Income is typically included here as a proxy for human capital. An alternative approach would be to estimate the present-value of future labor income directly as in Gomes and Smirnova (2022). However, this requires making additional assumptions on survival probabilities, expectations of future labor income and the relevant discount rates.

college degree, with only a slight decrease for post-graduate studies. This implies that individuals with higher educational attainment are more likely to participate in the stock market, underscoring the importance of financial literacy and education in enabling individuals to make informed financial decisions.

Multi-year treatment effect

As previously mentioned, the coefficient β_1 measures the treatment effect in the first year of treatment, which could be much less than 1 year of post-treatment period for several individuals. Given the well-documented inertia in household asset allocation decisions and consistent with a gradual learning channel, we would expect the treatment effect to accumulate over the first years after treatment.

Panel (a) of Figure 2 depicts the effect of DC plan eligibility on stock market participation over time. To facilitate economic interpretation, the effects are plotted relative to the unconditional mean stock market entry probability in the subsequent period, which equals 7% in the sample. Consistent with the prior hypothesis, the results reveal a cumulative effect over time, characterized by a hump-shaped pattern. The marginal effect increases until year three of the treatment. Eventually, the initial learning gradually decreases and stabilizes, and those most inclined to engage with equity investments have already entered the market.[26]

Additionally, individuals who were initially not eligible for a DC plan (the control group) may also increase their participation in the stock market over time. As they accumulate wealth, experience positive returns, or learn from the behavior of peers who are eligible for DC plans, non-participants may decide to invest in the stock market. This trend can potentially dampen the differences in participation rates between the treated and control groups, contributing to a leveling-off effect in participation differences.

Panel (b) of Figure 2 shows the cumulative effect over time. Consistent with portfolio inertia and gradual learning, the effect of DC on participation is even larger over longer horizons, and reaches 40.7% in 6 years. Thus, the effect of DC eligibility on stock market participation is characterized by an initial increase in participation as individuals gain knowledge, followed by a slow-down in the increase rate due to saturation effects, behavioral inertia, and increased participation among non-eligible individuals.

Notably, the economic magnitude of the effect can vary depending on the baseline used for interpretation, resulting in a range of estimates that may appear smaller or larger.

Panel (a) of Figure 3 plots the raw regression coefficients (marginal effects) estimated from Equation 10.[27] Panel (b) presents the cumulative sum of these estimated effects, showing that the cumulative effect on entry rates reaches 0.0274 six years after enrolling in a DC plan. Panel (c) illustrates the cumulative

[26] Importantly, Figure 2 indicates the absence of pre-trends, as shown by the estimates four, three and two years before DC plan enrollment ($\tau^{DC} = -3$, $\tau^{DC} = -2$, $\tau^{DC} = -1$). The base period is set to the year immediately preceding enrollment ($\tau^{DC} = 0$). The limited number of estimated and reported pre-periods is justified by the time-series dimension of the sample. Even when earlier periods are available for some individuals, the sample lacks sufficient variation in treatment within this group for the TWFE estimator to reliably infer and estimate effects. More on this issue can be found in Callaway and Sant'Anna (2021) and Sun and Abraham (2021).

[27] For example, the effect at $\hat{\tau}^{DC} = 1$ is the same as reported in Table 2 and equals 0.00274.

effect relative to the dynamic unconditional average stock market entry probability after τ years.[28] Using this interpretation, the long-term economic magnitude of the effect corresponds to a 9% increase in entry probability.

Figure 4 provides an alternative perspective on the magnitude of the effects. Panel (a) depicts the yearly effects relative to the dynamic unconditional mean entry probability in the sample for each τ, while Panel (b) shows the cumulative effects over time. Using this framework, the cumulative effect reaches a 63.5% increase in entry probability.

To summarize, the results across different specifications and interpretations confirm that having a DC plan increases the probability of stock market participation in non-retirement accounts from 9% to 63.5% depending on the economic interpretation. This provides evidence for the positive spillover effect of stock market exposure through DC pension plans.

4.2 Risky share

The regression results presented in Table 3 and Figure 5 show the impact of DC plan enrollment on the change in the risky share of individuals that were already stockholders before the treatment. Again, in the baseline specification I cluster standard errors at an individual level.[29] As before, in the Table I report the "year 1" treatment effect, while the Figure plots the dynamic effects over time, both marginal (panel a) and cumulative (panel b).

[INSERT TABLE 3 and FIGURE 5 HERE]

In Table 3 the coefficient on $\hat{\tau}^{DC} = 1$ is positive and statistically significant in both models (Δw and Δw^{active}), indicating that individuals enrolled in DC plans tend to increase their allocation to risky assets. Specifically, DC enrollment results in a 1.2 percentage point increase in the overall change in risky share and a 0.9 percentage point increase in the active change in risky share. This is relative to an unconditional average risky share of 43% in the first year.

Δw represents the overall change in risky share, encompassing both active rebalancing and passive changes due to asset price fluctuations. Δw^{active}, on the other hand, measures active rebalancing, focusing solely on intentional portfolio adjustments by individuals, excluding changes resulting from movements in asset prices. The positive coefficient on DC enrollment in the model for Δw^{active} suggests that individuals

[28] As shown in Appendix B, Figure A1a, the dynamic unconditional probabilities are 7.01% in the first year, 12.9% in the second year, 17.2% in the third year, 19.5% in the fourth year, 25.9% in the fifth year, and 32% by the sixth year. These probabilities are calculated by fixing a sample of non-participants in a given year and tracking their stock market participation over time, where entry equals one if a person participated at least once by year τ.

[29] There is a slight drop in significance under a more conservative clustering at age-year-region-occupation level. Reported in Table A2 in Appendix C.1.

are not only experiencing passive increases in risky assets but are also actively reallocating their portfolios to hold more risky investments after gaining DC plan access.

This result is consistent with DC plan enrollment providing individuals with increased trust and comfort in investing in riskier assets, leading them to adjust their financial portfolios accordingly. It is also consistent with individuals having decreasing risk aversion in preferences (evaluated over total financial wealth) and the tax optimization channel of Dammon et al. (2004).

The coefficient on log financial wealth ($\log FW_{t-1}$) is positive and significant, indicating that individuals with higher financial wealth are more likely to increase their exposure to risky assets. This is also consistent with decreasing relative risk aversion preferences and with the results in Bach et al. (2020).

As with the stock market entry decision, the effect is significantly larger over time, reflecting inertia in household portfolio rebalancing. The effect of DC on active change in risky share reaches 7.7 p.p. in 6 years.[30] In summary, the results show that DC plan enrollment encourages individuals to significantly increase their allocation towards risky assets.

5 Inspecting the Mechanism

Having found a positive effect of DC account enrollment on stock market entry and risky share, in this section I conduct additional tests that allow for a further understanding of the different channels at work. More precisely, I study the impact of the treatment on both portfolio diversification and savings/wealth accumulation.

5.1 Diversification

I assess portfolio diversification by analyzing the allocation of risky financial assets across mutual funds and individual stocks. If agents go beyond just learning about the benefits of stock market participation and holdings of risky assets, and acknowledge that it is important to hold a diversified portfolio, then they will tilt away from direct stock holdings towards mutual funds.[31]

Specifically, I examine whether individuals adjust their portfolios by increasing the proportion allocated to diversified mutual funds rather than individual stocks as share of risky assets, or financial wealth. The empirical model used for this analysis is:

$$\begin{aligned} \Delta F_t^{\%Risky} &= \alpha + \beta DC_{it} + \theta X_{it} + \gamma F_i + I(\text{year}_t) + \varepsilon_{it}, \\ \Delta F_t^{\%FW} &= \alpha + \beta DC_{it} + \theta X_{it} + \gamma F_i + I(\text{year}_t) + \varepsilon_{it}. \end{aligned} \tag{12}$$

[30] Figure 5 reflects the effects relative to unconditional mean of risky share.
[31] Low-fee Exchange-Traded Funds (ETF) were barely existent in this sample period.

Here, $\Delta F_t^{\%}$ represents the change in the share of mutual funds within individual i's portfolio between time $t-1$ and t. The coefficient β captures the effect of holding a defined contribution (DC) plan on diversification behavior. X_{it} denotes time-varying characteristics, F_i indicates time-invariant individual attributes, and $I(\text{year}_t)$ represents year fixed effects. The error term is denoted by ε_{it}. I estimate the regression conditional on stock market participation in both the previous and current periods.

A positive β, indicates that individuals with access to DC plans are more likely to diversify their investments beyond pension holdings and increase the proportion of their portfolios held in mutual funds. This outcome would align with the informational channel hypothesis, whereby individuals learn about the benefits of investing in diversified portfolios.

Alternatively, the introduction of DC plans could lead to a reduction in the share of mutual funds in non-pension portfolios, as individuals may perceive their pension funds, which are often diversified by default, as sufficient diversification. In this case, the coefficient β would be negative. This could be attributed to a substitution effects or mental accounting, where individuals categorize pension wealth separately from other financial wealth, thus potentially lowering the perceived need to diversify their non-pension investments.

As an alternative measure, I also estimate a model for the probability of buying mutual funds as opposed to direct investments in individual stocks:

$$P(Buy_{it}^{F}) = \alpha + \beta DC_{it} + \theta X_{it} + \gamma F_i + I(year_t) + \varepsilon_{it} \tag{13}$$

In this model, $P(Buy_{it}^{F})$ represent the probabilities of buying mutual funds for individual i at time t. The coefficient β measures the impact of having a DC plan on these behaviors. The variable X_{it} includes time-varying individual characteristics, F_i represents time-invariant individual characteristics, and $I(year_t)$ captures year fixed effects. ε_{it} is the error term.

These regressions aim to capture how DC plan exposure affects individuals' active diversification decisions—whether they are more inclined to buy mutual funds instead of directly investing in individual stocks, or to shift between asset classes by buying or selling. A positive β for $P(Buy_{it}^{Funds})$ would indicate that individuals with DC plans are more likely to allocate their new investments into mutual funds, possibly reflecting increased financial literacy and a preference for diversified investments due to their retirement plan exposure.

Table 4 reports the estimation result for Equations 12 and 13. The probability to buy mutual funds increases by 2.22% (relative to an unconditional mean of probability to buy funds which equals 63%) when enrolled in a DC plan. I also find an increase in the $\Delta F_t^{\%FW}$ (0.9 p.p. relative to an unconditional mean), while $\Delta F_t^{\%Risky}$ decreases (0.1 p.p relative to an unconditional mean). These results suggest that investors learn about funds, but still maintain a preference for individual stocks in non-pension accounts.

[INSERT TABLE 4 HERE]

5.2 Wealth effect

Swedish occupational DC plans are fully funded by the employer. When individuals are enrolled in the DC plan, they start receiving an employee contribution into their account and do not make any investments themselves. Therefore, it is natural to expect that this will lead to the crowding-out of private retirement savings. In this subsection, I first test for this channel and then repeat the stock market entry regressions without controlling for changes in wealth. If individuals are indeed reducing their non-retirement savings, the monetary participation cost (MPC) channel would predict a reduction in stock market entry in regressions where we do not control for changes in wealth. Such results can therefore shed further light on the underlying mechanisms and, in particular, on the role of MPC. I test whether DC enrollment decreases private savings in the following specification:

$$\Delta FW_{it} = \alpha + \sum_{j=-3}^{-1} \beta_j I[\hat{\tau}^{DC}=j] + \beta_1 I[\hat{\tau}^{DC}=1] + \sum_{j=2}^{6} \beta_j I[\hat{\tau}^{DC}=j] + \\ + \theta X_{it} + I[a_{it}] + I[y_t] + \varepsilon_{it}, \quad (14)$$

where ΔFW_{it} is measured by $\Delta FW/Y$, $\Delta \log FW_t$ or $\Delta_g FW_t$.[32]

The regression results in Table 5 show the impact of DC plan enrollment on various financial wealth measures.

[INSERT TABLE 5 HERE]

The first column presents the effect of treatment on the log of the financial wealth to income ratio ($\Delta FW/Y$). The coefficient for $\hat{\tau}^{DC} = 1$ is negative and significant (-0.003), indicating that individuals enrolled for a DC plan have a lower growth in their financial wealth to income ratio as compared to those without such a plan.

The second column examines the log change in financial wealth over two periods. The $\hat{\tau}^{DC} = 1$ coefficient is negative and significant (-0.011), implying that having a DC plan is associated with a marginal decline in the change of financial wealth. The third column presents the results for the growth in financial wealth. The $\hat{\tau}^{DC} = 1$ coefficient is negative and significant (-0.101), similar to the effect for $\Delta \log FW_t$, but larger in magnitude (due to the different scaling of the variable).

Overall, across all three measures I find strong evidence of a crowding-out effect from DC wealth to non-retirement savings. To further inspect this effect, I calculate the average change in the ratio of occupational DC contributions over income in the sample[33] which equals 4.65%. Comparing this with the effect of

[32] All the other controls are similar to the baseline specifications for stock market entry and change in risky share.

[33] The data does not explicitly provide DC account values, but I get the occupational DC contributions following

treatment on the log of the financial wealth to income ratio of -0.3%, I conclude that even though some crowding out of the liquid financial wealth is present, the total effect on savings in the financial wealth including DC accounts is positive.

In the presence of monetary participation costs (MPCs), this reduction in non-retirement wealth effect is an opposing force for the stock market entry probability of those enrolled in a DC plan. If this was the only channel driving stock market participation, then we should actually observe lower stock market entry for those in the treatment group, or a null effect in regressions that control for changes in wealth. My baseline regressions explicitly control for those changes, thus isolating the role of informational-driven participation costs (IPCs).

In this section I repeat those estimations but without including change in wealth as an explanatory variable. More precisely I estimate the following regression (same as Eq. 10):

$$P(Entry_{it}) = \alpha + \sum_{j=-3}^{-1} \beta_j I[_{\hat{\tau}^{DC}=j}] + \beta_1 I[_{\hat{\tau}^{DC}=1}] + \sum_{j=2}^{6} \beta_j I[_{\hat{\tau}^{DC}=j}] + \\ + \theta X_{it} + I[a_{it}] + I[y_t] + \varepsilon_{it}$$

If MPCs are important, then we should observe a smaller coefficient on the treatment, potentially even negative if the MPC channel is more important here than the reduction in IPC.

The results are shown in Table 6. The coefficient on the treatment variable is now smaller economically and not significant statistically in line with monetary participation costs. However, it is still positive, reflecting that the reduction in IPCs is still the dominant force, as well as consistent with the fact that there is a small drop in liquid financial wealth (outweighted by a much bigger increase in total financial wealth due to occupational DC contributions).

[INSERT TABLE 6 HERE]

5.3 Alternatives to Dynamic DiD

Sun and Abraham (2021) (hereafter SA) show that, in the presence of staggered treatment timing and treatment effect heterogeneity, two-way fixed effects dynamic effect estimates for one relative-time period are contaminated by the causal effects of other relative-time periods in the estimation sample.[34]

To address these concerns, I employ the approach proposed by Callaway and Sant'Anna (2021) (hereafter CS) to correct the estimations for this potential bias. Both SA and CS suggest robust solutions; however,

the institutional details provided in Appendix A, following the approach discussed in Calvet, Campbell, Gomes, and Sodini (2023a) and implemented in Calvet, Campbell, Gomes, and Sodini (2019).

[34] See Baker, Larcker, and Wang (2022) for a comprehensive discussion on the biases in staggered difference-in-differences and approaches to address them.

the latter is more suitable for my setup as it provides greater flexibility in settings without a never-treated group, allowing the use of not-yet-treated observations instead.

CS introduce a disaggregated causal parameter called the group-time average treatment effect (GATT), which is the average treatment effect for group g at time t, where a "group" is defined by the time period when units are first treated. An attractive feature of the GATT parameters is that they do not impose restrictions on heterogeneity with respect to observed covariates, the period in which units are first treated, or the evolution of treatment effects over time. Consequently, these easy-to-interpret causal parameters can be directly used to learn about treatment effect heterogeneity. Additionally, the method allows for the conditional parallel trends assumption, thereby incorporating covariates, which are essential in both participation and risky share empirical models.

I estimate the regressions following the steps in Callaway and Sant'Anna (2021), utilizing the *csdid* Stata package (Rios-Avila, Callaway, and Sant'Anna, 2021). The results for the event study/dynamic effects on the probability of stock market entry, the change in risky share, and the active change in risky share are reported in columns (1), (2), and (3) of Table 7.

[INSERT TABLE 7 HERE]

The model estimates all the dynamic effects (from four years before to six years after DC enrollment) using the Doubly Robust Inverse Probability Weighting (DRIPW) estimation method, with individuals who have not yet enrolled in the occupational DC plan serving as the control group. The estimator accommodates unbalanced panel data, employing repeated cross-section estimators, with standard errors clustered at the individual level. The specifications include a set of controls similar to those reported in the baseline results in Tables 2 and 3.

Firstly, the parallel trends assumption holds for all three dependent variables, as the average of the pre-treatment estimates Pre_{avg} are not statistically significant.[35] Secondly, the average of the post-treatment effects Post_{avg} of DC enrollment are positive and significant for both the probability of stock market entry (equivalent to a 63% increase on average relative to the unconditional mean of entry probability) and the active change in risky share (around 3.7 percentage points relative to the unconditional mean of risky share).

Regarding the dynamic patterns, the effect on the active change in risky share is slightly smaller during the first year after DC enrollment ($\hat{\tau}^{DC} = 1$) but catches up to similar magnitudes in subsequent periods. The effect on stock market entry is positive but not statistically significant in the first year; however, it becomes highly pronounced, both economically and statistically, during the second year of enrollment ($\hat{\tau}^{DC} = 2$) and

[35] Note that due to differences in the estimation samples—Column (1) includes non-participants in the previous period, while Columns (2) and (3) focus on participants in both the previous and current periods—the model estimates a different number of leads (2 versus 4). This difference is driven by the sufficiency of observations and treatment variation within each group.

remains significant at $\hat{\tau}^{DC} = 6$.[36]

This analysis confirms that the baseline results for the participation decision and risky share persist[37] after properly controlling for staggered treatment using the Callaway and Sant'Anna (2021) estimator, which additionally allows for testing and confirmation of the parallel pre-trend. This further confirms the causal nature of the estimated effects.

6 Evidence from the US

In this section I repeat my analysis in the U.S. context. The U.S. setting does not provide a clean identification since I cannot exploit exogenous plan assignment as in the Swedish setting. Furthermore, the sample size is much smaller since I have to rely on survey data as opposed to the full population tax registry. On the other hand, the data covers a more recent sample period.

6.1 Institutional setting

Retirement plans in the United States are structured through a combination of government and employer-sponsored programs. These plans can broadly be categorized into two main types: DB plans and DC plans, but hybrid plans also exist.

DB plans used to be the main vehicle for retirement savings in the U.S., both in the public and private sector.[38] Over time, DB plans have become less common in the private sector due to their high costs and complexity.[39] Nonetheless, they remain prevalent in the public sector, where they continue to provide secure retirement income for many government employees.[40] However, in the past two decades, there has been a noticeable shift towards DC plans as the predominant retirement savings vehicle in the U.S. among private-sector employers, as shown in Figure 6. In DC plans employees contribute a share of their pre-tax income to an individual account with employers often making additional contributions through matching programs, up to a certain limit.[41] Unlike DB plans, the investment risk in DC plans is borne by the employee. The

[36] The magnitudes are not directly comparable with the ones in Table 2 and Figure 4 as the model is estimated with least squares in this case following the approach suggested by CS in contrast to probit regression used in the former.

[37] The results are similar for all other specifications and dependent variables and are available upon request.

[38] Under these plans, employers promise to pay employees a specific monthly benefit upon retirement, determined by a formula that typically takes into account factors such as salary history, years of service, and the employee's age at retirement. The employer is responsible for funding these plans and bears all the investment risk. These benefits are usually paid out as a lifetime annuity, providing retirees with a steady income stream.

[39] In March 2023, only 15 percent of private industry workers had access to a defined benefit plan (Bureau of Labor Statistics (2024)).

[40] In March 2016, 75 percent of state and local government workers participated in defined benefit pension plans. Of these workers, 57 percent participated in frozen defined benefit plans, or plans that are not open to new employees (Bureau of Labor Statistics (2017)).

[41] There are several types of DC plans. The most common is the 401(k) plan, which is offered by private-sector employers. Similarly, 403(b) plans are available to employees of public schools, non-profit organizations, and cer-

retirement benefit is not predetermined but instead depends on the amount contributed and the performance of the investments chosen by the employee.

[INSERT FIGURE 6 HERE]

6.2 Data

To analyze the link between pension plan design and stock market participation decisions outside retirement plan in the US, I use 15 waves of Health and Retirement Study (HRS) data covering the period from 1992 through 2020. The sample in HRS is nationally representative of the American population 50 years old and above, and surveys approximately 12,000 to 20,000 people biannually. The survey is a panel study, and on average it tracks a person for 9 consecutive waves.

6.2.1 Sample Selection

I start with 42,406 individuals (29,478 households) from the RAND HRS 2020 file. Firstly, I filter out everyone above age 65, to make sure that the sample includes only those who did not reach the full retirement age to avoid issues relating to the decumulation of assets due retirement following the previous literature (Poterba, Venti, and Wise (1996), Engen et al. (1994), Engen, Gale, and Scholz (1996) and Benjamin (2003)). I also set a minimum age of 50 to make sure there are enough observations at each age. This leaves 29,805 individuals (21,143 households).

Around 55% of the working sample participates in an employer-sponsored pension plan as shown in Figure 7. Next, I keep only those who had a pension account provided by the employer at least once over the surveyed period - 14,467 respondents (from 12,252 households) were eligible for such an account. As the line "filtered" in Figure 7 shows, in any particular wave around 90% of working people in the truncated sample have a work-related pension plan.

[INSERT FIGURE 7 HERE]

As discussed in Section 6.4, the dependent variable in the analysis is a stock market entry decision, thus, I require at least two consecutive observations for each individual in the sample. This additional filter leaves me with 13,623 individuals (from 11,478 households).

I additionally drop the respondents who were retired, self-employed or changed job. I also require that a household has minimal financial savings of 50$ and a household income of 5,000$ (2010 prices). This final filter leaves 10,525 individuals (from 8,710 households) corresponding to 28,387 observations.

tain ministers, operating in much the same way as 401(k) plans. 457 plans cater to state and local government employees, as well as some non-profit workers.

6.2.2 Pension plan data

The Health and Retirement Study collects a large range of pension-related data (section G on Employment before 2000, section J on Employment starting in 2002 and section J2 on Pension starting in 2016). The survey provides information on plan history for up to 4 plans, plan type and policy, contributions (self- and employer-made), accumulated benefits, and how the funds in the plan account are invested.

The question on the plan type provides three options, namely, defined benefit (formula), defined contribution (account) or mixed. I assign DB plan type presence if the person reported that respective type for at least one of the reported plans. Identifying DC plans is less straightforward, as some patterns in the responses suggest potential inconsistency in the data. To make sure the DC plans are correctly identified, I rely on additional information about plans available, namely whether the individual reported positive contributions made by employer and employee, and if DC account value is positive. I also impute DC or DB account presence if the information is missing in the current survey wave, but such an account is reported in both the previous and the next wave (conditional on the person not changing employer during this period).

Figure 6 shows the evolution of DB and DC plan shares in the selected sample of HRS pension plan participants.[42] DB plans in the sample peaked at 76% in the 1996 and decreased almost two-folds to 45% by 2020. DC plans, on the contrary, have been actively growing from 58% to 90% between 1994 and 2010, and slightly decreased to 81% in 2020.

Next, I identify switchers and first-time entrants to the DC plans. Switchers are those who had DB pension plan before and now have a DC plan (this could be due to a change in the plan, or an additional plan).

Figure 8 illustrates the share of participants who either switched to a defined contribution (DC) plan or entered a DC plan for the first time, over the period from 1992 to 2020, conditional on participating in any pension plan. As this Figure shows, the share of participants who switched to a DC plan starts at around 8% in 1992 and generally declines over time, reaching its lowest point of about 2% in 2016, with some peak fluctuations in 2006, 2012, and 2018. Similarly, the share of first-time entrants into DC plans follows a downward trend, consistently remaining lower than the switchers' share throughout the period.

[INSERT FIGURE 8 HERE]

6.2.3 Financial Variables and Other Controls

In the analysis I include different measures of wealth, such as liquid wealth, financial wealth and total wealth. Financial wealth includes both risky and riskless assets. Risky assets include shares of stock in publicly held corporations, mutual funds, or investment trusts and corporate, municipal, government, or foreign bonds,

[42] Some people have multiple plans and both types, so the sum of shares may exceed 100%

or any bond funds (outside IRA and Keogh accounts). Riskless assets sum the value of checking, savings, and money market accounts, and value of CDs, government savings bonds, and treasury bills. Stock market participation is defined as equal to 1 for an individual if risky assets has a positive value and 0 otherwise.

Liquid wealth is financial wealth less uncollaterized debt (i.e. credit card balances, medical debts, life insurance policy loans, loans from relatives). Total wealth is liquid wealth plus the net value of house equity (house value minus current mortgage value).

Savings in IRA and Keogh accounts are tracked separately in the HRS, so there is a separate IRA wealth variable, and an IRA dummy to indicate if a person has any such accounts, and risky share in IRA, if any.

Total family income is total income of the head of household and their spouse or partner for the last calendar year. It includes respondent and spouse earnings, pensions and annuities, SSI and Social Security Disability, Social Security retirement, unemployment and workers compensation, other government transfers, household capital income, and other income.

I deflate all nominal variables to 2010 using the consumer CPI series from the St. Louis Federal Reserve. I then take logarithms and first differences to obtain growth rates. The wealth and income variables are winsorized at the 1st and 99th percentiles.

Following the literature, I include "life-cycle controls" and "preference shifters" such as age, age squared, gender, race, education, change in the marriage status, change in the children dummy, (change in) home ownership status, region of residence.

6.3 Descriptive statistics

Table 9 presents summary statistics comparing key demographic and financial characteristics between individuals in the Defined Benefit (DB) and Defined Contribution (DC) groups. Each variable is accompanied by sample sizes (N), mean values for both groups, the difference in means (diff^{DB-DC}), standard errors, t-values, and p-values.

[INSERT TABLE 9 HERE]

In the demographic category, the mean age for both groups is similar, with a negligible and statistically insignificant difference. The gender distribution shows a slight but marginally significant difference, with the DB group having a marginally higher proportion of males. There is a notable and significant difference in the race variable, with the DB group having a higher average racial index. The proportion of married individuals is slightly lower in the DB group compared to the DC group, and this difference is statistically significant. The average education level is significantly lower in the DB group, and union membership is considerably higher, with a significant difference indicating that more DB participants are unionized.

For the wealth measures, both mean financial wealth (FW) and liquid wealth (LW) are significantly lower in the DB group, with substantial differences of approximately 33 and 32 thousand dollars, respectively.

However, the growth rates of financial and liquid wealth, measured as changes in their logarithmic values, show no significant differences between the groups. Total wealth (TW) is also lower in the DB group, with a significant gap. Family income (FAMINC) and ownership of assets also show significant differences, with the DB group having lower values. Furthermore, the proportion of individuals holding an IRA is notably lower in the DB group.

Participation in the stock market is higher among the DC group, with significant differences in both overall participation and entry rates. Specifically, the entry rate among non-participants and the overall entry rate are higher for the DC group. However, the exit rate among participants does not differ between groups, while the overall exit rate is significantly higher in the DB group.

Finally, conditional response statistics indicate that the conditional risky share (cond. RS) is slightly lower for the DB group, and this difference is statistically significant. However, changes in the risky share, both in absolute and active terms, do not exhibit significant differences between the groups. Overall these comparisons confirm that there are some significant differences between the two groups, as expected.

6.4 Empirical Setup

In the US setting, I focus on the change in the type of individual's retirement plan from DB to DC, conditional on the fact they have remained in the same job. To further account for personal saving preferences, I include as controls, variables such as changes in financial wealth and income, home ownership, and demographic factors.

The main empirical test aims to evaluate how the transition from a DB plan (or no pension plan) to a DC plan affects individuals' likelihood of entering the stock market and risky share for current stock market participants. So, the analysis focuses on a sample of individuals who, at time $t-2$, either had a DB plan or no pension and did not have a DC plan. By time t, these individuals may have switched to a DC plan. By analogy, I use the similar dynamic DiD setting, however, the variation comes from the staggered changes in the employer-specific pension rules.

The key variable of interest is the presence of a DC plan for period $\hat{\tau}^{DC} = j$ at time t, with control variables including individual characteristics, financial factors, and time effects. The objective is to determine whether the shift to a DC plan increases the probability of entering the stock market, compared to those who remained in a DB plan.

$$P(Entry_{it}) = \alpha + \sum_{j=-4}^{-2} \beta_j I[_{\hat{\tau}^{DC}=j}] + \beta_1 I[_{\hat{\tau}^{DC}=1}] + \sum_{j=4}^{12} \beta_j I[_{\hat{\tau}^{DC}=j}] + \\ + \theta X_{it} + I[a_{it}] + I[y_t] + \varepsilon_{it} \quad (15)$$

$Entry_{it}$ represents whether individual i enters the stock market at time t, this means that individual did not participate in the stock market before ($Partic_{t-1,t} = 0$). $\hat{\tau}^{DC}$ denotes years before/after getting DC (age_{it} - $age_t^{rule} + 1$). Indicator $I[\hat{\tau}^{DC} = j]$ equals 1 if $\hat{\tau}^{DC} = j$ is true. Coefficient β_j captures the effect of being treated (having a DC plan) for j periods between time $t-1$ and t on the likelihood of entering the stock market at time t. X_{it} is vector of time-varying characteristics that are not perfectly correlated across individuals. $I[a_{it}]$ is set of age dummies. $I[y_t]$ represents time fixed effects to account for any temporal factors that could influence stock market entries over the period. ε_{it} is a (regression) residual.

As in the Swedish setting, a similar analysis is conducted for the change in (active) risky share for stock market participants:

$$\Delta\omega_{it}^{(a)} = \alpha + \sum_{j=-4}^{-2} \beta_j I[\hat{\tau}^{DC}=j] + \beta_1 I[\hat{\tau}^{DC}=1] + \sum_{j=4}^{12} \beta_j I[\hat{\tau}^{DC}=j] + \\ + \theta X_{it} + I[a_{it}] + I[y_t] + \varepsilon_{it} \quad (16)$$

6.5 Results

Table 10 presents regression results analyzing the effect of DC pension plan enrollment on stock market entry over various time horizons using HRS data. The estimates are displayed in two sets: the Baseline model (Column 1) and the Baseline model with an additional control for IRA ownership (Columns 2). The dependent variable measures the likelihood of stock market entry, and the results are reported as marginal effects. The standard errors are presented in parentheses below the coefficient estimates, and clustered at individual level.[43]

[INSERT TABLE 10 HERE]

For specific time horizons, the effect of DC plan enrollment on stock market entry is noteworthy. At $\hat{\tau}^{DC} = 4$, the marginal effect is positive and statistically significant at the 1% and 10% levels across the Baseline and IRA-controlled models, respectively. This suggests a marked increase in the probability of stock market entry four years after DC plan enrollment. At $\hat{\tau}^{DC} = 10$ and $\hat{\tau}^{DC} = 12$, the effect is even more pronounced, with statistically significant increases at the 1% level. Specifically, the effect at $\hat{\tau}^{DC} = 10$ reaches a substantial magnitude, indicating a robust influence of DC plan enrollment.

The wealth growth variable, $\Delta \log FW_t$, consistently shows a significant positive relationship with stock market entry, emphasizing the importance of financial wealth in predicting stock market behavior. Additionally, the inclusion of an IRA control variable demonstrates a significant and positive impact, indicating

[43] Alternative clustering at age-year level does not change the significance and reported in Table A3 in Appendix C.1.

that IRA ownership is a strong predictor of stock market participation.

The results indicate that DC pension plan enrollment has a temporal impact on stock market entry, with significant effects manifesting several years after enrollment.

Analogously, 11 presents regression results analyzing the effect of DC pension plan enrollment on risky share over various time horizons using HRS data. There is some evidence of the positive effect on the (active) change in risky share for stock market participants. Although there is no statistical significance in any horizon[44], the effect at $\hat{\tau}^{DC} = 6$ and $\hat{\tau}^{DC} = 10$ is economically meaningful (around 3.65 and 5 percentage point increase relative to unconditional risky share in the first year, respectively, and summing to 10.9 percentage point over 12 years).

[INSERT TABLE 11 HERE]

To sum up, although the identification is much weaker in case of the US setting, and the therefore the results are prone to endogeneity and reverse causality concerns, and the sample size is small, I find some evidence of positive effect of a DC account enrollment on stock market entry and risky share.

7 Conclusion

This paper examines the impact of Defined Contribution (DC) pension plan enrollment on individuals' non-pension investment behavior by exploiting exogenous changes in Swedish occupational pension rules. Utilizing detailed data from the Swedish Tax Registry, the study addresses selection concerns and finds that DC enrollment significantly boosts stock market entry probability, with an initial increase of 3.9% and a cumulative effect of 40.7% over the first six years. These results hold even after controlling for various observables, including changes in financial wealth, highlighting the importance of information costs in explaining the limited stock market participation observed in the data.

For individuals who were already stockholders, exposure to DC plans raises the share of risky assets in their liquid portfolios. This finding is consistent with a learning channel effect, decreasing relative risk aversion (DRRA) preferences, or tax optimization strategies. Interestingly, the impact on diversification is mixed: while DC enrollment increases the likelihood of buying mutual funds and raises their share relative to financial wealth, individuals decrease their share of funds over risky assets.

Overall, these findings demonstrate that DC plans positively influence stock market engagement outside retirement accounts by enhancing financial literacy, manifested in reduced stock market participation costs. The results underscore the potential of DC plans to shape broader financial behavior beyond retirement savings and highlight the importance of designing pension plans that promote financial literacy and market participation.

[44]The result is unchanged under alternative clustering at age-year level reported in Table A4 in Appendix C.1.

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Figures

Figure 1: Policy Changes in Fixed Age Rule for DC Enrollment

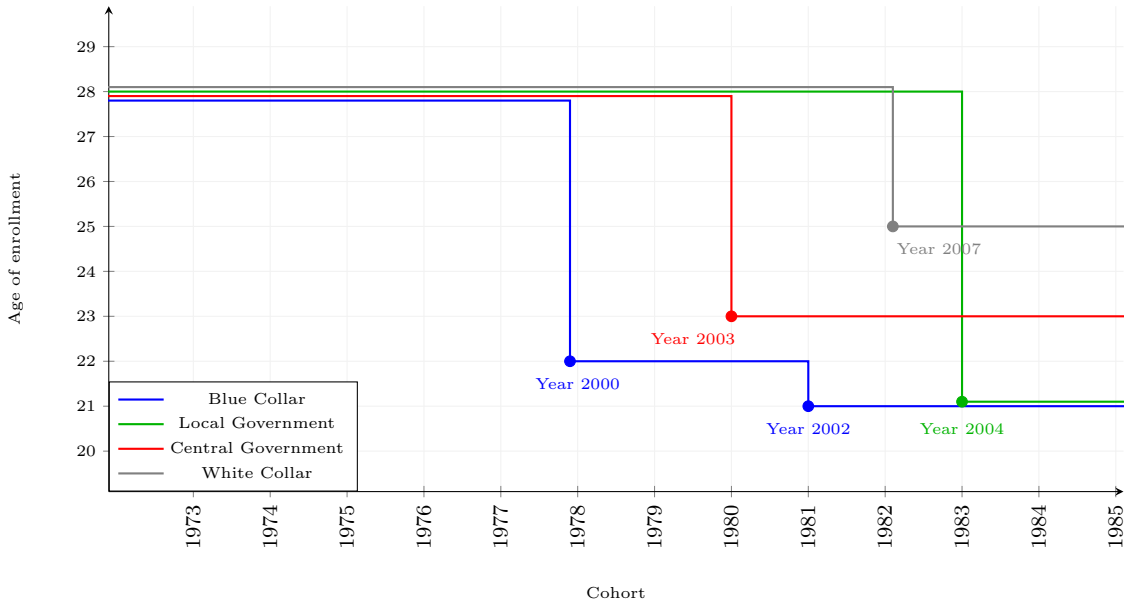
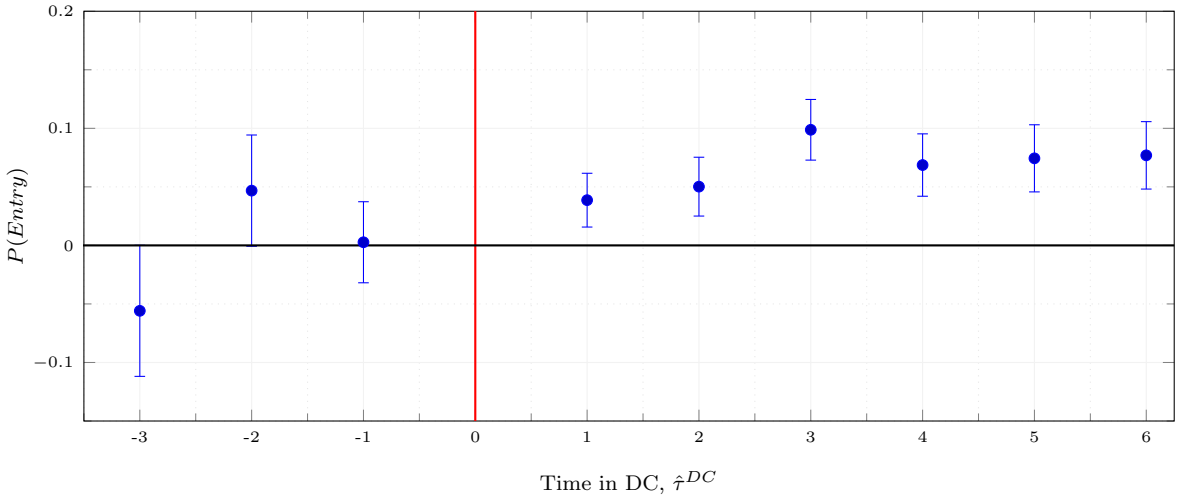
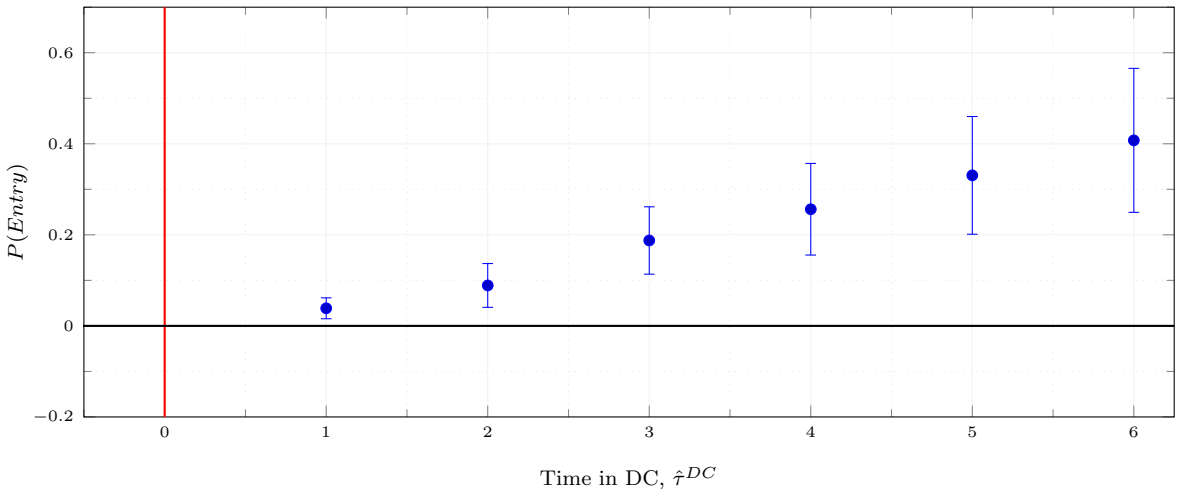


Figure 1 presents the enrollment eligibility age for defined contribution (DC) pension plans across different occupational groups and birth cohorts in Sweden, summarizing the policy changes detailed in Appendix A. Distinct colors represent Blue Collar, Local Government, Central Government, and White Collar workers. The x-axis indicates birth cohorts first affected by the policy change, while the y-axis displays the eligibility age for enrollment. Key policy changes are marked by dots, showing the years when eligibility ages were revised. For example, Blue Collar workers saw their eligibility age reduced to 22 in 2000 and further to 21 in 2002. The lines illustrate that the treatment—the change in eligibility age—varies by both birth cohort and occupational group.

Figure 2: Stock Market Entry by Time in DC: (a) Yearly effect; (b) Cumulative effect relative to static unconditional mean of entry probability



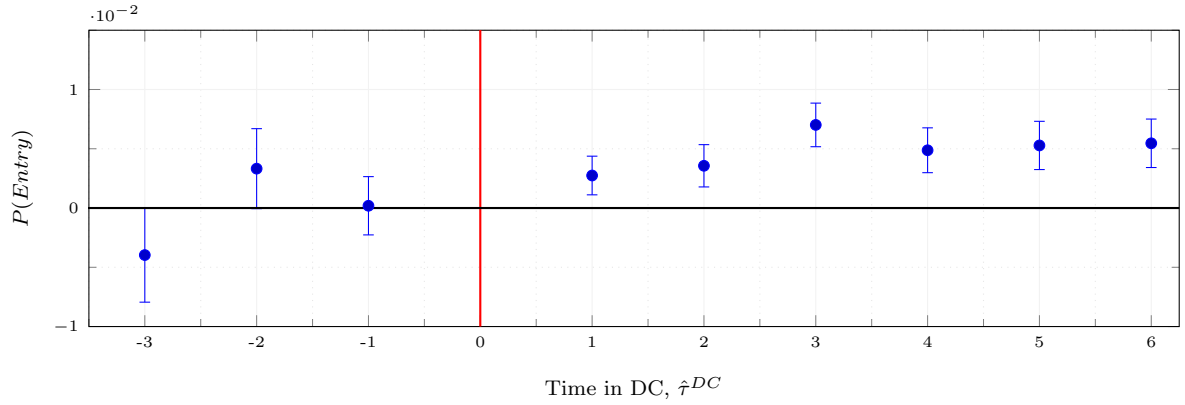
(a) Regression coefficients



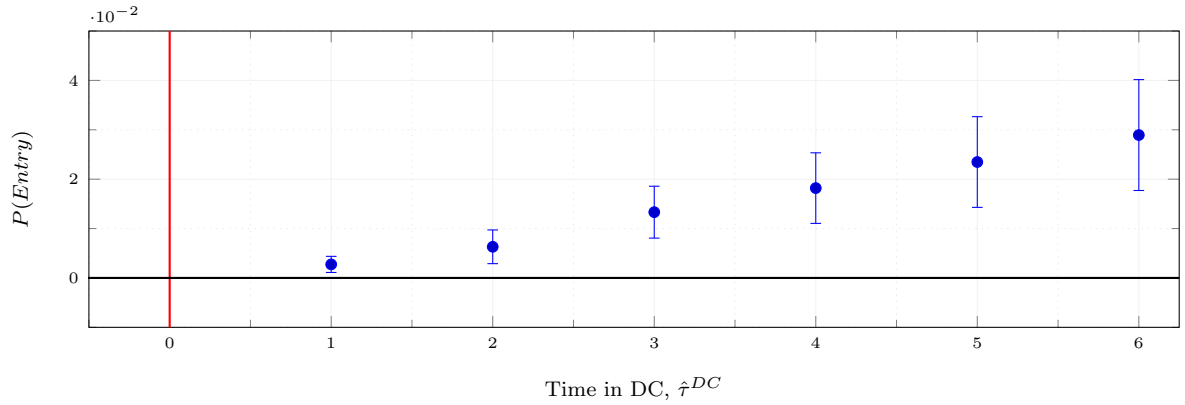
(b) Cumulative effect

Figure 2 visualizes the estimation results for the dynamic effects from regression equation (10): $P(Entry_{it}) = \alpha + \sum_{j=-3}^{-1} \beta_j I[\hat{\tau}^{DC}=j] + \sum_{j=1}^{6} \beta_j I[\hat{\tau}^{DC}=j] + \theta X_{it} + I[a_{it}] + I[y_t] + \varepsilon_{it}$, where the dependent variable is the probability of stock market entry $P(Entry_{it})$. The independent variables include indicators for time relative to DC plan enrollment ($\hat{\tau}^{DC} = j$), life-cycle controls X_{it}, age fixed effects $I[a_{it}]$, and year fixed effects $I[y_t]$. To facilitate economic interpretation, the effects (regression coefficients β_j) are plotted relative to the *unconditional mean static one-year stock market entry probability of of 7%*. The vertical red line at $\hat{\tau}^{DC} = 0$ indicates the year preceding DC plan enrollment. Panel (a) displays the estimated effects, representing the change in the probability of stock market entry at different times before and after DC plan enrollment. Panel (b) shows the cumulative effect of DC plan enrollment on the probability of stock market entry over time. Both panels also show the 95% confidence intervals.

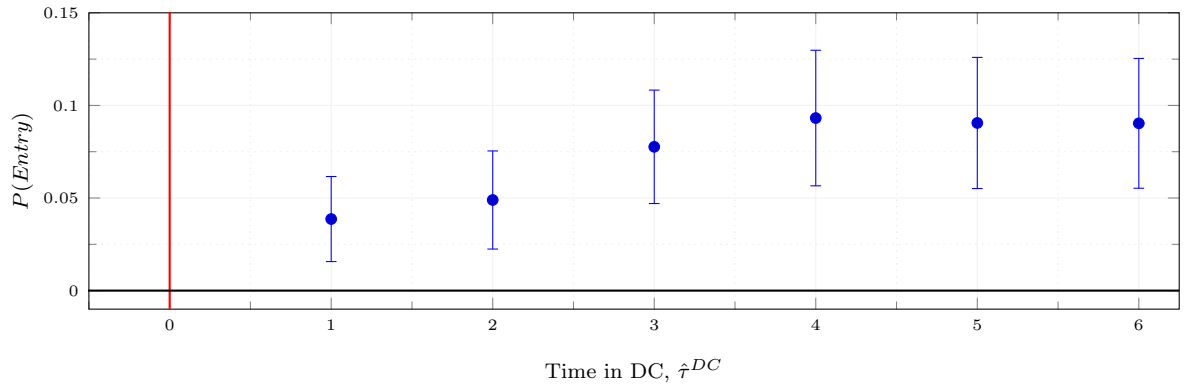
Figure 3: Stock Market Entry by Time in DC: (a) Regression coefficients; (b) Cumulative sum of coefficients; (c) Cumulative effect relative to dynamic unconditional mean entry probability



(a) Regression coefficients



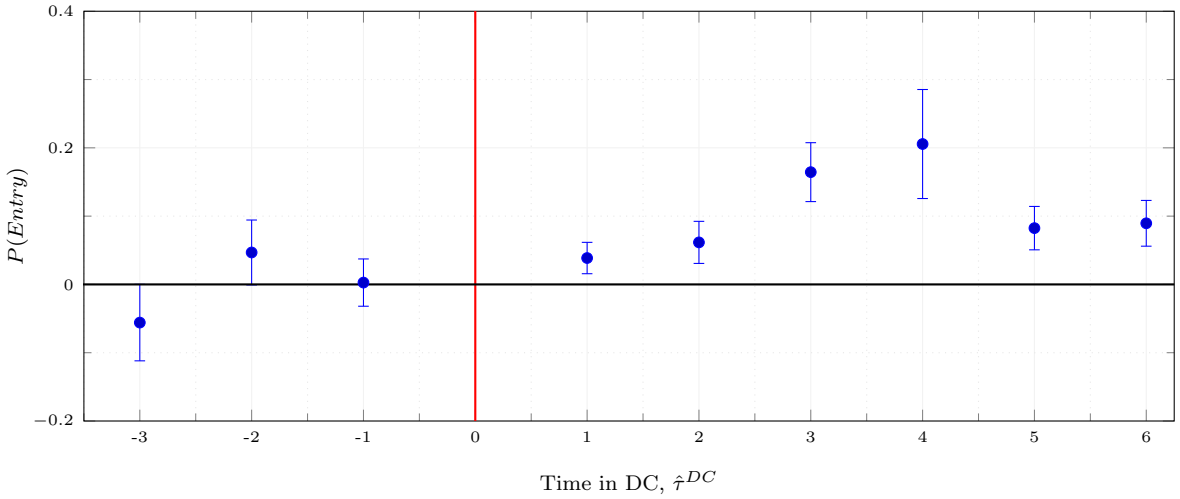
(b) Cumulative effect



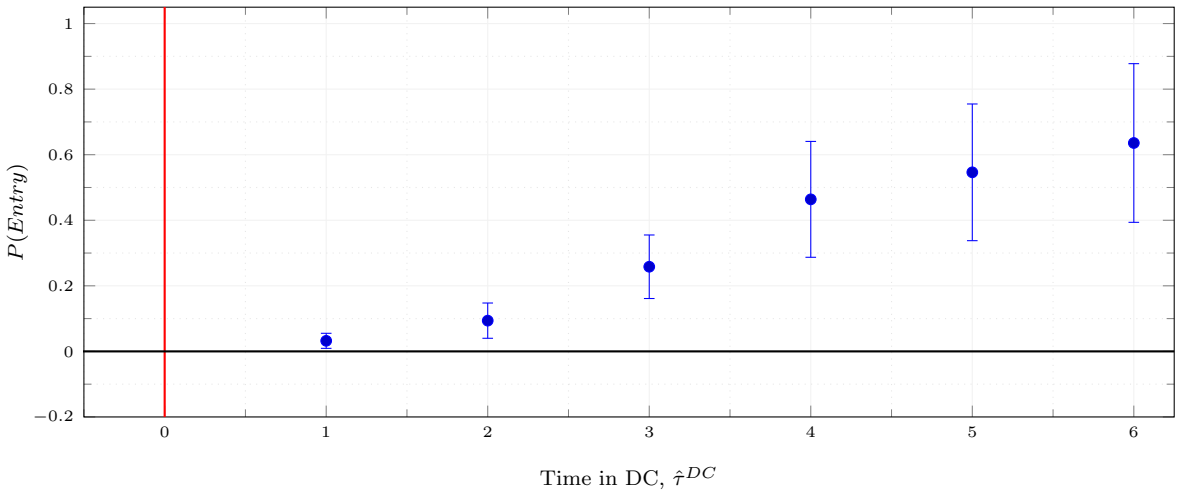
(c) Cumulative effect relative to dynamic unconditional mean entry probability

Figure 3 visualizes the estimation results for the dynamic effects from regression equation (10): $P(Entry_{it}) = \alpha + \sum_{j=-3}^{-1} \beta_j I[\hat{\tau}^{DC}=j] + \sum_{j=1}^{6} \beta_j I[\hat{\tau}^{DC}=j] + \theta X_{it} + I[a_{it}] + I[y_t] + \varepsilon_{it}$, where the dependent variable is the probability of stock market entry $P(Entry_{it})$. The independent variables include indicators for time relative to DC plan enrollment ($\hat{\tau}^{DC} = j$), life-cycle controls X_{it}, age fixed effects $I[a_{it}]$, and year fixed effects $I[y_t]$. The vertical red line at $\hat{\tau}^{DC} = 0$ indicates the year preceding DC plan enrollment. Panel (a) displays the estimated (raw) coefficients, representing the change in the probability of stock market entry at different times before and after DC plan enrollment. Panel (b) shows the time-cumulative of the (raw) coefficients in panel (a). To facilitate economic interpretation, panel (c) shows the cumulative effect from panel (b) relative to the unconditional average stock market entry probability after τ years (shown in Figure A1b in Appendix B). All panels also show the 95% confidence intervals.

Figure 4: Stock Market Entry by Time in DC: (a) Yearly effect; (b) Cumulative effect relative to dynamic unconditional mean of entry probability



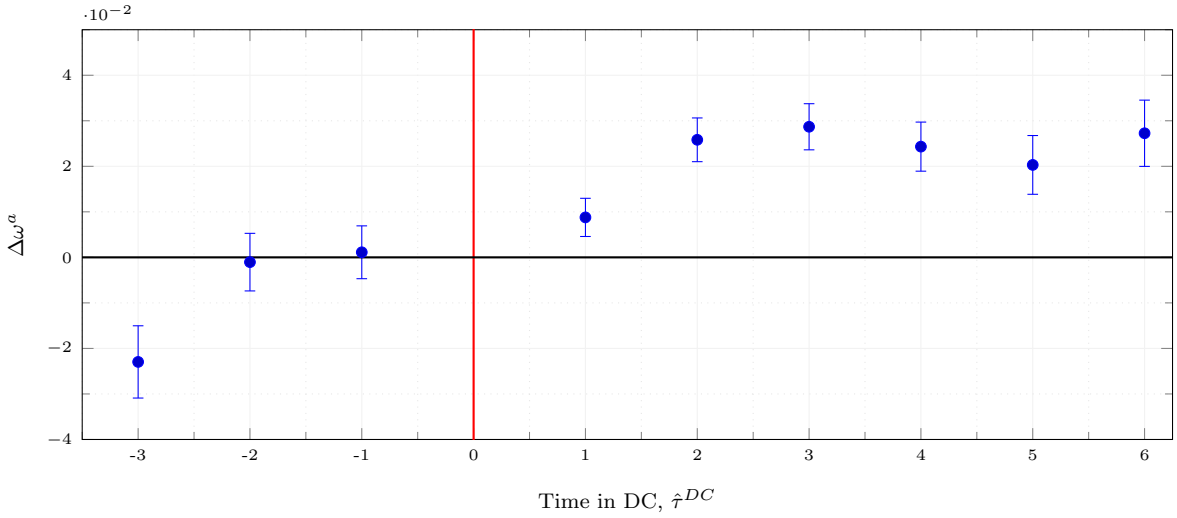
(a) Regression coefficients



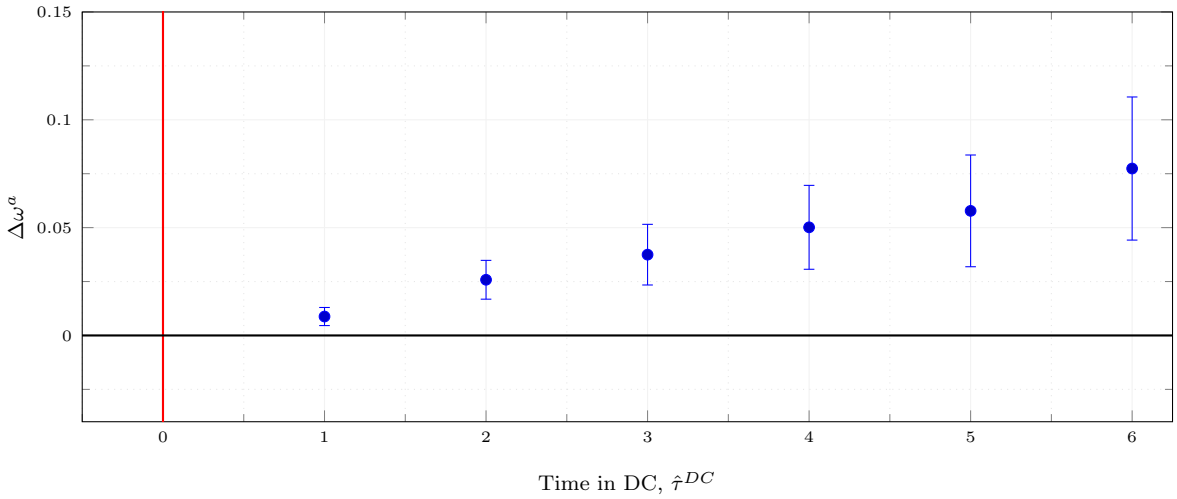
(b) Cumulative effect

Figure 4 visualizes the estimation results for the dynamic effects from regression equation (10): $P(Entry_{it}) = \alpha + \sum_{j=-3}^{-1} \beta_j I[\hat{\tau}^{DC}=j] + \sum_{j=1}^{6} \beta_j I[\hat{\tau}^{DC}=j] + \theta X_{it} + I[a_{it}] + I[y_t] + \varepsilon_{it}$, where the dependent variable is the probability of stock market entry $P(Entry_{it})$. The independent variables include indicators for time relative to DC plan enrollment ($\hat{\tau}^{DC} = j$), life-cycle controls X_{it}, age fixed effects $I[a_{it}]$, and year fixed effects $I[y_t]$. To facilitate economic interpretation, the effects (regression coefficients β_j) are plotted relative to the unconditional average stock market entry probability after τ years (shown in Figure A1b in Appendix B). The vertical red line at $\hat{\tau}^{DC} = 0$ indicates the year preceding DC plan enrollment. Panel (a) displays the estimated effects, representing the change in the probability of stock market entry at different times before and after DC plan enrollment. Panel (b) shows the time-cumulative of the effects in panel (a). Both panels also show the 95% confidence intervals.

Figure 5: Active change in Risky Share by Time in DC: (a) Regression coefficients; (b) Cumulative effect



(a) Regression coefficients



(b) Cumulative effect

Figure 5 presents the estimation results for the dynamic effects from regression equation (11): $\Delta\omega_{it}^{(a)} = \alpha + \sum_{j=-3}^{-1} \beta_j I[\hat{\tau}^{DC}=j] + \sum_{j=1}^{6} \beta_j I[\hat{\tau}^{DC}=j] + \theta X_{it} + I[a_{it}] + I[y_t] + \varepsilon_{it}$, where the dependent variable is the active change in risky share $\Delta\omega_{it}^{a}$ of individual i at time t. The independent variables include indicators for time relative to DC plan enrollment ($\hat{\tau}^{DC} = j$), life-cycle controls X_{it}, age fixed effects $I[a_{it}]$, and year fixed effects $I[y_t]$. To facilitate economic interpretation, the effects (regression coefficients β_j) are plotted relative to the unconditional mean of the risky share in the first year (43%). The vertical red line at $\hat{\tau}^{DC} = 0$ indicates the year preceding DC plan enrollment. Panel (a) displays the estimated effects, representing the change in the active risky share at different times before and after DC plan enrollment. Panel (b) shows the cumulative effect of DC plan enrollment on the active risky share over time. Both panels also show the 95% confidence intervals.

Figure 6: Share of DB and DC over time, conditional on participating in a pension plan

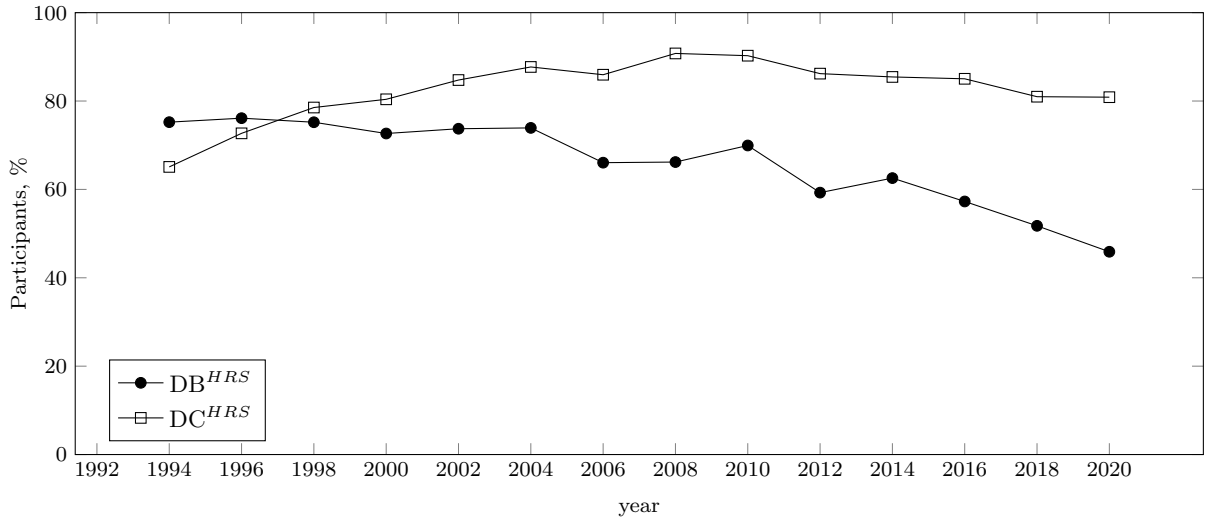


Figure 6 illustrates the evolution of the proportion of DB and DC pension plans over time among participants in pension plans, based on data from the Health and Retirement Study (HRS). The solid black lines represent the shares of DB and DC plans in the HRS sample, with circles and squares indicating DB and DC plans, respectively. The x-axis displays the years from 1988 to 2020 (with data available for every even year corresponding to the HRS survey wave), and the y-axis shows the percentage of participants in the plan. The figure shows a clear trend over time: the share of participants with DB plans has generally decreased, while the share with DC plans has increased.

Figure 7: Participation in employer-provided pension plans, conditional on working

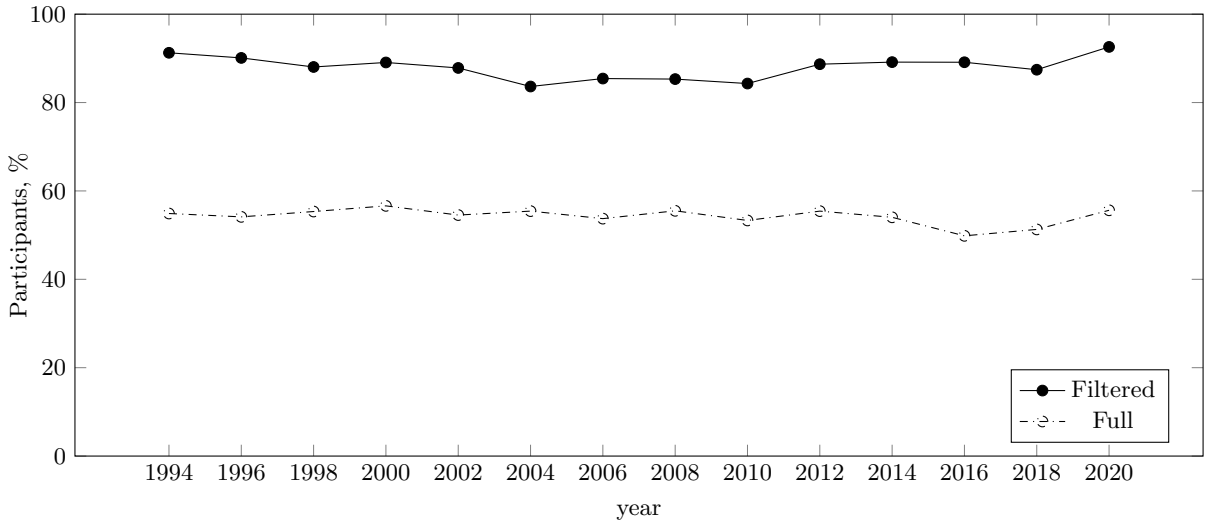


Figure 7 illustrates the percentage of workers participating in employer-provided pension plans over the period from 1994 to 2020, conditional on being employed. Among all employed individuals in the HRS dataset, participation rates start at 54.89% in 1994 and fluctuating slightly over the years, reaching 55.62% in 2020, as shown by the dashed line with empty circle markers. Filtered sample includes those who had a pension account provided by the employer at least once over the surveyed period. The participation rates in this group are consistently high, starting at 91.26% in 1994, experiencing a slight decline to 83.63% in 2004, and then rising to 92.59% by 2020, as reflected by the solid line with solid circle markers.

Figure 8: Share of DC switchers and first entrants over time, conditional on participating in a pension plan.

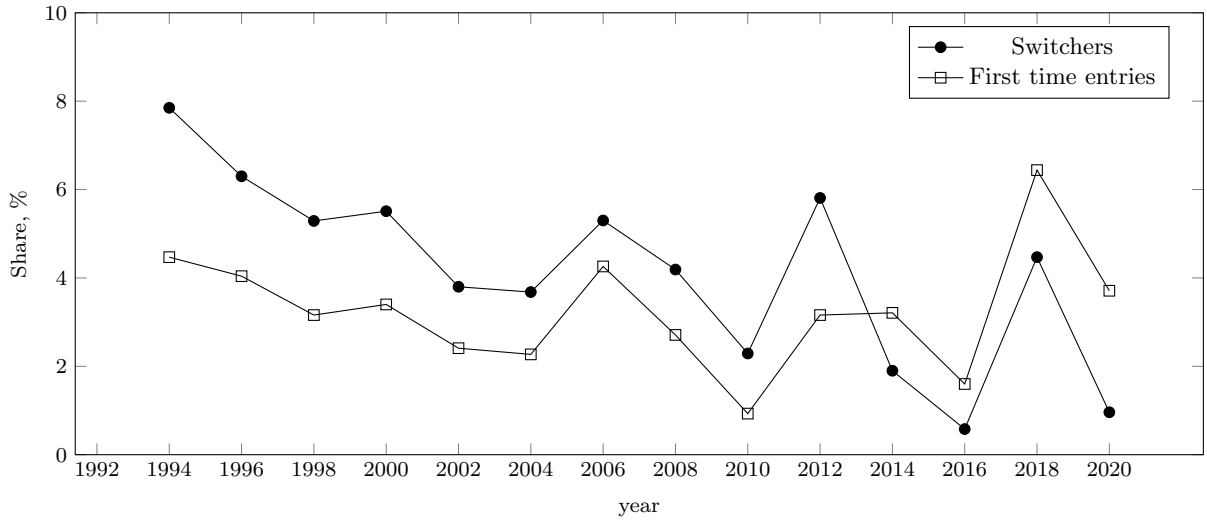


Figure 8 illustrates the share of participants who either switched to a defined contribution (DC) plan or entered a DC plan for the first time over the period from 1992 to 2020. The share is conditional on participating in any pension plan in both the current and previous wave for switchers, or participating in the current wave and having no employer-based retirement plan in the previous wave for first-time DC entrants.

Tables

Table 1: Descriptive Statistics for Sweden

(a) Full Sample

	(1) Kids	(2) Marital	(3) Edu	(4) Y	(5) Partic	(6) Entry	(7) Exit	(8) FW	(9) $\Delta FW/Y$	(10) $\Delta \log FW$	(11) $\Delta_g FW$
N	3.62m	3.62m	3.60m	3.62m	3.62m	1.55m	1.79m	3.62m	3.32m	3.34m	3.34m
Mean	0.31	0.22	1.51	176,565	0.53	0.07	0.05	80,395	-0.05	0.10	0.50
SD	0.46	0.45	0.90	75,159	0.50	0.26	0.23	171,240	0.57	0.76	1.76
p25	0.00	0.00	1.00	130,433	0.00	0.00	0.00	13,726	-0.07	-0.23	-0.20
p50	0.00	0.00	1.00	172,360	1.00	0.00	0.00	25,580	0.01	0.15	0.16
p75	1.00	0.00	2.00	216,237	1.00	0.00	0.00	73,982	0.06	0.42	0.53

(b) Stock Market Participants ($t-1$ and t)

	(1) w	(2) Δw	(3) Δw^{active}	(4) $F^{\%Risky}$	(5) $F^{\%FW}$	(6) $P(Buy_t^F)$
N	1.69m	1.69m	1.69m	1.69m	1.69m	1.69m
Mean	0.43	-0.02	0.02	0.76	0.32	0.63
SD	0.29	0.21	0.22	0.37	0.28	0.48
p25	0.17	-0.10	-0.06	0.61	0.06	0.00
p50	0.41	-0.00	0.01	1.00	0.27	1.00
p75	0.68	0.07	0.10	1.00	0.53	1.00

Table 1 presents descriptive statistics for the Swedish sample of individuals aged between 18 and 34 used in the study. Panel (a) shows statistics for the full sample, including variables such as number of children (*Kids*), marital status (*Marital*), education level (*Edu*), income (Y), stock market participation indicator (*Partic*), entry and exit into the stock market (*Entry* and *Exit*), financial wealth (FW), change in financial wealth to income ratio ($\Delta FW/Y$), log-difference financial wealth ($\Delta \log FW$), growth in financial wealth ($\Delta_g FW$) reported in Columns (1) to (11). Panel (b) focuses on individuals who are stock market participants at times $t-1$ and t, and includes variables such as risky share of financial wealth (w), change in risky share (Δw), active change in risky share (Δw^{active}), proportion of risky assets in mutual funds ($F^{\%Risky}$), proportion of financial wealth in mutual funds ($F^{\%FW}$), and probability of buying mutual funds ($P(Buy_t^F)$) reported in Columns (1) to (6). The statistics reported are the number of observations (N), mean, standard deviation (SD), and the 25th (p25), 50th (p50), and 75th (p75) percentiles. Monetary values are in Swedish Krona (SEK).

Table 2: Regression result for Stock Market Entry and DC plan Eligibility.

	(1)	(2)	(3)
$\hat{\tau}^{DC} = 1$	0.002***	0.003***	0.003***
	(0.001)	(0.001)	(0.001)
$\Delta \log FW_t$	0.056***	0.055***	0.056***
	(0.000)	(0.000)	(0.000)
$\log Y_t$	0.041***	0.038***	0.037***
	(0.001)	(0.001)	(0.001)
Occupation (Base is White collar)			
Central Gov	-0.030***	-0.029***	-0.029***
	(0.002)	(0.002)	(0.002)
Local Gov	-0.044***	-0.040***	-0.042***
	(0.001)	(0.001)	(0.001)
Blue Collar	-0.031***	-0.029***	-0.031***
	(0.001)	(0.001)	(0.001)
Education (Base is no high school)			
High School	0.017***	0.015***	0.015***
	(0.001)	(0.001)	(0.001)
Some College	0.029***	0.025***	0.025***
	(0.001)	(0.001)	(0.001)
Graduated College	0.053***	0.047***	0.047***
	(0.001)	(0.001)	(0.001)
Post-Grad	0.041***	0.037***	0.038***
	(0.005)	(0.005)	(0.005)
Marriage status (Base is not married)			
Married		-0.019***	-0.019***
		(0.001)	(0.001)
Divorced		-0.022***	-0.021***
		(0.002)	(0.002)
Widowed		0.014	0.015
		(0.024)	(0.024)
Have kids		-0.015***	-0.015***
		(0.001)	(0.001)
Owner		0.012***	0.012***
		(0.000)	(0.000)
Year and Age FE	Yes	Yes	Yes
Region FE	No	No	Yes
Pseudo R2	0.147	0.150	0.151
N	1,504,753	1,504,753	1,504,753

Individual-clustered standard errors in parentheses
Estimates are ME evaluated at sample averages
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2 presents the estimation results for the dynamic effects from regression equation (10) estimated using Probit model: $P(Entry_{it}) = \alpha + \sum_{j=-3}^{-1} \beta_j I[_{\hat{\tau}^{DC}=j}] + \beta_1 I[_{\hat{\tau}^{DC}=1}] + \sum_{j=2}^{6} \beta_j I[_{\hat{\tau}^{DC}=j}] + \theta X_{it} + I[a_{it}] + I[y_t] + \varepsilon_{it}$, where the dependent variable is the probability of stock market entry $P(Entry_{it})$, so I estimate the regression conditional on no stock market participation in previous period. The independent variables include indicators for time relative to DC plan enrollment ($\hat{\tau}^{DC} = j$), life-cycle controls X_{it}, age fixed effects $I[a_{it}]$, and year fixed effects $I[y_t]$. Columns (1), (2) and (3) show specifications with different sets of controls, progressively adding covariates such as occupation, education, marital status, ownership status, region of residentship. All specifications in this table control for log-change in wealth ($\Delta \log FW_t$) and log income ($\log Y_t$). I only report the treatment effect in the first year of treatment (coefficient β_1), while the full set of dynamic effects is shown in Figure 4. The table shows the marginal effects evaluated at sample averages. Standard errors are clustered at individual level.

Table 3: Regression Result for Risky Share and DC Plan enrollment.

	(1) Δw_t	(2) Δw_t^{active}
$\hat{\tau}^{DC} = 1$	0.005***	0.004***
	(0.001)	(0.001)
$\log FW_{t-1}$	0.016***	0.018***
	(0.000)	(0.000)
$\log Y_t$	0.000***	0.000***
	(0.000)	(0.000)
Occupation (Base is White collar)		
Central Gov	0.004***	0.001
	(0.001)	(0.001)
White Collar	-0.005***	0.005***
	(0.001)	(0.001)
Blue Collar	-0.002	-0.001
	(0.001)	(0.001)
Education (Base is no high school)		
High School	-0.006***	-0.005***
	(0.001)	(0.001)
Some College	-0.005***	-0.000
	(0.001)	(0.001)
Graduated College	-0.015***	-0.012***
	(0.001)	(0.001)
Post-Grad	-0.015***	-0.012***
	(0.003)	(0.004)
Marriage status (Base is not married)		
Married	-0.000	0.001*
	(0.001)	(0.001)
Divorced	0.009**	0.006
	(0.003)	(0.004)
Widowed	0.039	0.014
	(0.030)	(0.031)
Have kids	0.008***	0.008***
	(0.000)	(0.000)
Owner	-0.008***	-0.005***
	(0.001)	(0.001)
Year and Age FE	Yes	Yes
Region FE	Yes	Yes
Adj. R2	0.0551	0.0341
N	1,666,819	1,666,819

Individual-clustered standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3 presents the estimation results for the dynamic effects from regression equation (11) estimated for the subsample of stock market participants in both previous and current period: $\Delta\omega_{it}^{(a)} = \alpha + \sum_{j=-3}^{-1} \beta_j I[\hat{\tau}^{DC}=j] + \beta_1 I[\hat{\tau}^{DC}=1] + \sum_{j=2}^{6} \beta_j I[\hat{\tau}^{DC}=j] + \theta X_{it} + I[a_{it}] + I[y_t] + \varepsilon_{it}$, where the dependent variable is the (active) change in risky share $\Delta\omega^(a)_{it}$ of individual i at time t. The independent variables include indicators for time relative to DC plan enrollment ($\hat{\tau}^{DC} = j$), life-cycle controls X_{it}, age fixed effects $I[a_{it}]$, and year fixed effects $I[y_t]$. Column (1) shows the result of the change in risky share ($\Delta\omega_{it}$), and column (2) shows the estimations for the active change in risky share ($\Delta\omega_{it}^a$). Both regressions include the full set of covariates (wealth and income controls, occupation, education, marital status, and ownership status). I only report the treatment effect in the first year of treatment (coefficient β_1), while the full set of dynamic effects is shown in Figure 5. The table shows the marginal effects evaluated at sample averages. Standard errors are clustered at individual level.

Table 4: Regression Results for Funds-Related Variables

	(1) $P(Buy_t^F)$	(2) $\Delta F_t^{\%Risky}$	(3) $F_t^{\%FW}$
DC	0.014***	-0.001*	0.003***
	(0.002)	(0.000)	(0.001)
$\Delta \log FW_t$	0.138***	0.002***	-0.078***
	(0.001)	(0.000)	(0.000)
$\log Y_t$	-0.031***	-0.001***	-0.026***
	(0.001)	(0.000)	(0.000)
Occupation (Base is White collar)			
Central Gov	-0.012***	0.002***	0.001*
	(0.003)	(0.000)	(0.001)
White Collar	-0.024***	-0.003***	0.000
	(0.003)	(0.001)	(0.001)
Blue Collar	-0.046***	-0.001***	-0.001**
	(0.003)	(0.001)	(0.001)
Education (Base is no high school)			
High School	0.070***	-0.001*	-0.002***
	(0.003)	(0.000)	(0.001)
Some College	0.081***	-0.001**	-0.002***
	(0.003)	(0.001)	(0.001)
Graduated College	0.135***	-0.000	-0.005***
	(0.003)	(0.001)	(0.001)
Post-Grad	0.115***	-0.002	-0.002
	(0.009)	(0.002)	(0.002)
Marriage status (Base is not married)			
Married	-0.009***	-0.000	-0.002***
	(0.002)	(0.000)	(0.000)
Divorced	-0.059***	-0.001	0.001
	(0.006)	(0.001)	(0.001)
Widowed	0.055	-0.005	0.012
	(0.035)	(0.010)	(0.010)
Have kids	-0.011***	-0.001***	-0.001*
	(0.001)	(0.000)	(0.000)
Owner	0.004***	-0.003***	-0.009***
	(0.001)	(0.000)	(0.000)
Year and Age FE	Yes	Yes	Yes
Region FE	No	No	Yes
ME	Yes	No	No
R2	0.0359	0.0074	0.0984
N	1,679,259	1,677,804	1,677,804

Individual-clustered standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4 presents the estimation results for the diversification measures: probability to buy funds $P(Buy_{it}^F)$ and share of funds in the portfolio $\Delta F_t^{\%}$. Column (1) shows the results for Equation (13): $P(Buy_{it}^F) = \alpha + \beta DC_{it} + \theta X_{it} + \gamma F_i + I(year_t) + \varepsilon_{it}$ estimated using Probit model. In columns (2) and (3) the left-hand side variable in the regression is the indicator for share of funds in the portfolio $\Delta F_t^{\%}$, either relative to risky asset holdings (column (2)) or to financial wealth (column (2)): $\Delta F_t^{\%} = \alpha + \beta DC_{it} + \theta X_{it} + \gamma F_i + I(\text{year}_t) + \varepsilon_{it}$ (Equation 12). The coefficient β captures the average treatment effect for the treated for holding a DC plan on diversification behavior. X_{it} denotes time-varying characteristics, F_i indicates time-invariant individual attributes, and $I(\text{year}_t)$ represents year fixed effects. The error term is denoted by ε_{it}. The covariates include income controls, occupation, education, marital status, and ownership status. I estimate the regression conditional on stock market participation in both the previous and current periods. The Column (1) in the table shows the marginal effects evaluated at sample averages. Standard errors are clustered at individual level.

Table 5: Regression Result for Wealth

	(1) $\Delta FW/Y_t$	(2) $\Delta \log FW_t$	(3) $\Delta_g FW_t$
$\hat{\tau}^{DC} = 1$	-0.003***	-0.011***	-0.101***
	(0.007)	(0.003)	(0.008)
$\log Y_t$	0.041***	0.038***	0.037***
	(0.001)	(0.001)	(0.001)
Occupation (Base is White collar)			
Central Gov	-0.041***	-0.038***	-0.114***
	(0.008)	(0.003)	(0.010)
White Collar	0.163***	0.010***	0.147***
	(0.009)	(0.003)	(0.011)
Blue Collar	0.068***	-0.019***	0.006
	(0.008)	(0.003)	(0.010)
Education (Base is no high school)			
High School	-0.004	-0.005***	0.031***
	(0.004)	(0.001)	(0.004)
Some College	-0.003	0.032***	0.093***
	(0.005)	(0.002)	(0.006)
Graduated College	0.037***	0.040***	0.146***
	(0.006)	(0.002)	(0.007)
Post-Grad	0.266***	0.186***	0.575***
	(0.028)	(0.009)	(0.032)
Marriage status (Base is not married)			
Married	0.019***	0.028***	0.072***
	(0.004)	(0.001)	(0.004)
Divorced	-0.001	0.004	0.012
	(0.009)	(0.003)	(0.010)
Widowed	0.792***	0.199***	1.226***
	(0.142)	(0.043)	(0.180)
Have kids	-0.035***	-0.030***	-0.086***
	(0.003)	(0.001)	(0.004)
Owner	0.003	-0.058***	-0.010***
	(0.003)	(0.001)	(0.004)
Year and Age FE	Yes	Yes	Yes
Region FE	Yes	Yes	Yes
Adj. R2	0.0577	0.1454	0.0657
N	1,509,542	1,522,456	1,522,456

Individual-clustered standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 5 presents the estimation results for the dynamic effects from regression Equation (14): $\Delta FW_{it} = \alpha + \sum_{j=-3}^{-1} \beta_j I[\hat{\tau}^{DC}=j] + \beta_1 I[\hat{\tau}^{DC}=1] + \sum_{j=2}^{6} \beta_j I[\hat{\tau}^{DC}=j] + \theta X_{it} + I[a_{it}] + I[y_t] + \varepsilon_{it}$, where ΔFW_{it} is measured by $\Delta FW/Y$ (column (1)), $\Delta \log FW_t$ (column (2)) or $\Delta_g FW_t$ (column (3)). The independent variables include indicators for time relative to DC plan enrollment ($\hat{\tau}^{DC} = j$), life-cycle controls X_{it}, age fixed effects $I[a_{it}]$, and year fixed effects $I[y_t]$. The covariates include income controls, occupation, education, marital status, and ownership status. I only report the treatment effect in the first year of treatment (coefficient β_1). Standard errors are clustered at individual level.

Table 6: Regression Result for Stock Market Entry: No FW Control

	(1)
$\hat{\tau}^{DC} = 1$	0.001
	(0.001)
$\Delta \log Y_t$	0.005***
	(0.000)
Occupation (Base is White collar)	
Central Gov	-0.042***
	(0.002)
Local Gov	-0.060***
	(0.001)
Blue Collar	-0.047***
	(0.001)
Education (Base is no high school)	
High School	0.016***
	(0.001)
Some College	0.022***
	(0.001)
Graduated College	0.048***
	(0.001)
Post-Grad	0.038***
	(0.004)
Marriage Status (Base is Not Married)	
Married	-0.015***
	(0.001)
Divorced	-0.011***
	(0.001)
Widowed	0.040**
	(0.016)
Have Kids	-0.013***
	(0.001)
Owner	0.011***
	(0.001)
Year and Age FE	Yes
Region FE	Yes
Adj. R2	0.0577
N	1,504,753

Individual-clustered standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 6 presents the estimation results for the dynamic effects from regression Equation (10) estimated using Probit model: $P(Entry_{it}) = \alpha + \sum_{j=-3}^{-1} \beta_j I[_{\hat{\tau}^{DC}=j}] + \beta_1 I[_{\hat{\tau}^{DC}=1}] + \sum_{j=2}^{6} \beta_j I[_{\hat{\tau}^{DC}=j}] + \theta X_{it} + I[a_{it}] + I[y_t] + \varepsilon_{it}$, where the dependent variable is the probability of stock market entry $P(Entry_{it})$. The independent variables include indicators for time relative to DC plan enrollment ($\hat{\tau}^{DC} = j$), life-cycle controls X_{it}, age fixed effects $I[a_{it}]$, and year fixed effects $I[y_t]$. So I estimate the regression conditional on no stock market participation in previous period. The specification is similar to the one in Column (3) of Table 2, with the exception of wealth control which is excluded from the covariates list in this case. I include log income ($\log Y_t$), occupation, education, marital status, ownership status, region of residentship as controls. I only report the treatment effect in the first year of treatment (coefficient β_1). The table shows the marginal effect evaluated at sample averages. Standard errors are clustered at individual level.

Table 7: Regression Result for Entry and Risky Share using Callaway and Sant'Anna (2021) Estimator.

	(1) $P(Entry_{it})$	(2) Δw_t	(3) Δw_t^{active}
$\hat{\tau}^{DC} = -4$		-0.043	-0.099
		(0.104)	(0.130)
$\hat{\tau}^{DC} = -3$		-0.078	-0.076
		(0.096)	(0.104)
$\hat{\tau}^{DC} = -2$	-0.055	0.003	0.011
	(0.082)	(0.008)	(0.010)
$\hat{\tau}^{DC} = -1$	-0.028***	0.003	0.002
	(0.009)	(0.004)	(0.004)
$\hat{\tau}^{DC} = 0$	0.002	0.000	0.004*
	(0.008)	(0.002)	(0.002)
$\hat{\tau}^{DC} = 1$	0.011	0.004***	0.003**
	(0.007)	(0.001)	(0.001)
$\hat{\tau}^{DC} = 2$	0.121***	0.006***	0.005***
	(0.033)	(0.002)	(0.002)
$\hat{\tau}^{DC} = 3$	0.005	0.014***	0.012***
	(0.011)	(0.002)	(0.003)
$\hat{\tau}^{DC} = 4$	-0.006	0.014***	0.009**
	(0.015)	(0.004)	(0.004)
$\hat{\tau}^{DC} = 5$	0.024	0.030***	0.037***
	(0.026)	(0.006)	(0.007)
$\hat{\tau}^{DC} = 6$	0.108***	0.031**	0.030*
	(0.028)	(0.016)	(0.017)
Group-Time Weighted Average Treatment Effect (GATT)			
Pre_{avg}	-0.027	-0.023	-0.031
	(0.028)	(0.029)	(0.034)
$Post_{avg}$	0.044***	0.016***	0.016***
	(0.012)	(0.004)	(0.004)
Year and Age FE	Yes	Yes	Yes
Region FE	Yes	Yes	Yes
Life-Cycle and Preference Controls	Yes	Yes	Yes
N	796,281	873,856	873,684

Individual-clustered standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 7 presents the estimation results for the dynamic effects from regression for stock market entry probability and the (active) change in risky share using Callaway and Sant'Anna (2021). The model estimates all the dynamic effects (from 4 years before getting a DC to 6 years after) using Doubly Robust IPW (DRIPW) estimation method, and individuals who did not get enrolled to the occupational DC yet as a control group. The estimator further assumes unbalanced panel data, with repeated cross-section estimators, but SEs clustered at individual level. The specifications use the conditional parallel trends assumption, and include a set of controls similar to models reported in the baseline result Tables 2 and 3.

Table 8: Number of DB to DC switchers and new entries to DC

year	(1) Switch	(2) Entry	(3) Total
1994	218	124	342
1996	145	93	238
1998	97	58	155
2000	123	76	199
2002	60	38	98
2004	47	29	76
2006	97	78	175
2008	65	42	107
2010	27	11	38
2012	127	69	196
2014	36	61	97
2016	8	22	30
2018	75	108	183
2020	13	50	63
Total	1,138	859	1,997

Table 8 provides detailed data on the number of individuals who switched from DB pension plans to DC pension plans, as well as new entries into DC plans, among the subsample of Health and Retirement Study (HRS) respondents during survey waves between 1994 and 2020. The column (1) (Switch) represents participants who transitioned from a DB plan to a DC plan within the given year. The column (2) (Entry) includes individuals who newly entered into a DC plan without prior participation in a DB plan within the dataset. The column (3) sums the number of switchers and new entrants for each year.

Table 9: Summary Statistics by DC Group

Variable	(1) N^{DB}	(2) N^{DC}	(3) $Mean^{DB}$	(4) $Mean^{DC}$	(5) $diff^{DB-DC}$	(6) Std Err	(7) t-value	(8) p-value
Demographics								
Age	4621	26418	57.893	57.855	0.037	0.056	0.65	0.501
Gender	4621	26418	0.546	0.533	0.013	0.008	1.65	0.098
Race	4616	26399	1.318	1.254	0.064	0.009	6.75	0.000
Married	4621	26418	0.762	0.783	-0.022	0.007	-3.25	0.001
Children	4621	26418	0.920	0.919	0.002	0.005	0.35	0.725
Education	4621	26416	3.662	3.767	-0.104	0.021	-5.00	0.000
Union	4423	25591	0.398	0.231	0.168	0.008	21.45	0.000
Wealth Measures								
FW	4621	26418	87.267	120.422	-33.154	5.654	-5.85	0.000
$\Delta \log FW$	4184	24434	0.135	0.111	0.025	0.022	1.10	0.261
LW	4621	26418	80.778	113.720	-32.943	5.668	-5.80	0.000
$\Delta \log LW$	3047	17915	0.139	0.114	0.025	0.026	0.95	0.341
TW	4621	26418	246.720	337.380	-90.660	10.335	-8.75	0.000
$\Delta \log TW$	3962	23095	0.095	0.104	-0.009	0.014	-0.60	0.550
FAMINC	4621	26418	103.877	122.845	-18.968	6.224	-3.05	0.003
$\Delta \log FAMINC$	4507	25829	0.032	0.025	0.007	0.009	0.70	0.479
Owner	4621	26418	0.865	0.891	-0.026	0.005	-4.90	0.000
IRA	4621	26418	0.527	0.686	-0.159	0.008	-20.20	0.000
Participation and Entry/Exit								
Participation	4621	26418	0.314	0.386	-0.072	0.007	-9.70	0.000
Entry (% non-partic)	3176	16089	0.128	0.166	-0.037	0.007	-5.70	0.000
Entry (% all)	4621	26418	0.088	0.101	-0.013	0.005	-2.85	0.005
Exit (% partic)	1358	9806	0.248	0.248	0.000	0.013	0.00	0.991
Exit (% all)	4621	26418	0.073	0.092	-0.019	0.004	-4.55	0.000
Conditional Response								
cond. RS	1450	10199	0.615	0.636	-0.021	0.009	-2.40	0.016
cond. ΔRS	1021	7374	0.014	0.013	0.001	0.009	0.05	0.953
cond. Δ^aRS	1021	7374	-0.009	-0.007	-0.002	0.009	-0.20	0.846

Table 9 presents summary statistics comparing individuals in Defined Benefit (DB) and Defined Contribution (DC) pension plans. Variables include demographics such as age, gender, race, marital status, number of children, education level, and union membership; wealth measures like financial wealth (FW), changes in log financial wealth (Δ log FW), liquid wealth (LW), changes in log liquid wealth (Δ log LW), total wealth (TW), changes in log total wealth (Δ log TW), family income (FAMINC), changes in log family income (Δ log FAMINC), home ownership status (Owner), and Individual Retirement Account ownership (IRA); participation and entry/exit rates in the stock market, including participation rate, entry rates among non-participants and all individuals, and exit rates among participants and all individuals; and conditional response measures such as conditional risky share (cond. RS), change in conditional risky share (cond. ΔRS), and active change in conditional risky share (cond. Δ^aRS). Columns report sample sizes (N^{DB}, N^{DC}), group means ($Mean^{DB}$, $Mean^{DC}$), differences in means ($diff^{DB-DC}$), standard errors, and p-values for the difference. Statistical significance is indicated by p-values less than 0.05.

Table 10: Regression results for DC Pension Plan effect on Stock Market Entry

	Baseline	IRA Control
	(1)	(2)
$\hat{\tau}^{DC} = -4$	0.004	-0.008
	(0.020)	(0.021)
$\hat{\tau}^{DC} = -2$	0.003	-0.003
	(0.021)	(0.021)
$\hat{\tau}^{DC} = 2$	0.002	-0.002
	(0.012)	(0.012)
$\hat{\tau}^{DC} = 4$	0.032***	0.021*
	(0.012)	(0.012)
$\hat{\tau}^{DC} = 6$	0.006	-0.003
	(0.015)	(0.015)
$\hat{\tau}^{DC} = 8$	0.028*	0.018
	(0.017)	(0.017)
$\hat{\tau}^{DC} = 10$	0.082***	0.067***
	(0.020)	(0.020)
$\hat{\tau}^{DC} = 12$	0.032***	0.023***
	(0.007)	(0.008)
$\Delta \log FW_t$	0.079***	0.079***
	(0.002)	(0.002)
IRA		0.077***
		(0.006)
Life Cycle Controls	Yes	Yes
Preference Controls	Yes	Yes
Year and Regions FE	Yes	Yes
N	17,370	16,862

Individual-clustered standard errors in parentheses
Marginal effects evaluated at sample averages
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 10 presents the regression results for the Equation 15: $P(Entry_{it}) = \alpha + \sum_{j=-4}^{-2} \beta_j I[_{\hat{\tau}^{DC}=j}] + \beta_1 I[_{\hat{\tau}^{DC}=1}] + \sum_{j=4}^{12} \beta_j I[_{\hat{\tau}^{DC}=j}] + \theta X_{it} + I[a_{it}] + I[y_t] + \varepsilon_{it}$ assessing the effect of DC pension plan enrollment on the probability of stock market entry in the HRS data for the US. Sample includes only individuals who did not participate in the stock market in the previous period, so the dependent variable $P(Entry_{it})$ is a binary indicator of whether an individual enters the stock market. The key independent variables are time indicators relative to DC plan enrollment, denoted by $\hat{\tau}^{DC} = j$, where j represents years before ($j < 0$) or after ($j > 0$) DC enrollment. Column (1) shows the baseline specification, while Column (2) includes an additional control for IRA ownership. Models incorporate life cycle controls, preference controls, and fixed effects for year and region. The coefficients for $\hat{\tau}^{DC}$ variables indicate the change in the probability of stock market entry at specific time intervals relative to DC plan enrollment. The reported effects are marginal effects are evaluated at the sample averages. Standard errors clustered at the individual level are reported in parentheses.

Table 11: Regression results for DC Pension Plan effect on Risky Share

	$\Delta\omega$		$\Delta\omega^a$	
	(1)	(2)	(3)	(4)
$\hat{\tau}^{DC} = -4$	0.009	0.008	0.008	0.007
	(0.023)	(0.023)	(0.023)	(0.023)
$\hat{\tau}^{DC} = -2$	0.040	0.039	0.038	0.037
	(0.026)	(0.026)	(0.026)	(0.026)
$\hat{\tau}^{DC} = 2$	0.006	0.005	0.005	0.004
	(0.016)	(0.016)	(0.015)	(0.015)
$\hat{\tau}^{DC} = 4$	-0.006	-0.007	-0.006	-0.007
	(0.015)	(0.015)	(0.015)	(0.015)
$\hat{\tau}^{DC} = 6$	0.025	0.024	0.023	0.022
	(0.017)	(0.017)	(0.017)	(0.017)
$\hat{\tau}^{DC} = 8$	0.009	0.008	0.009	0.008
	(0.019)	(0.019)	(0.019)	(0.019)
$\hat{\tau}^{DC} = 10$	0.032	0.031	0.031	0.031
	(0.027)	(0.027)	(0.027)	(0.027)
$\hat{\tau}^{DC} = 12$	0.001	0.000	0.001	0.000
	(0.007)	(0.007)	(0.007)	(0.007)
$\Delta \log FW_t$	0.079^{***}	0.079^{***}	0.079^{***}	0.079^{***}
	(0.002)	(0.002)	(0.002)	(0.002)
IRA		0.009		0.009
		(0.009)		(0.009)
Life Cycle Controls	Yes	Yes	Yes	Yes
Preference Controls	Yes	Yes	Yes	Yes
Year and Regions FE	Yes	Yes	Yes	Yes
N	8,379	8,379	8,379	8,379

Individual-clustered standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 11 presents the regression results for the Equation 16: $\Delta\omega_{it}^{(a)} = \alpha + \sum_{j=-4}^{-2} \beta_j I[_{\hat{\tau}^{DC}=j}] + \beta_1 I[_{\hat{\tau}^{DC}=1}] + \sum_{j=4}^{12} \beta_j I[_{\hat{\tau}^{DC}=j}] + \theta X_{it} + I[a_{it}] + I[y_t] + \varepsilon_{it}$ assessing the effect of DC pension plan enrollment on the change in (active) risky share for stock market participants in the HRS data for the US. Sample includes only individuals who participate in the stock market in the previous and current period. The key independent variables are time indicators relative to DC plan enrollment, denoted by $\hat{\tau}^{DC} = j$, where j represents years before ($j < 0$) or after ($j > 0$) DC enrollment. Column (1) shows the baseline specification, while Column (2) includes an additional control for IRA ownership for the change in risky share. Columns (3) and (4) present the results for the active change in risky share, accordingly. Models incorporate life cycle controls, preference controls, and fixed effects for year and region. The coefficients for $\hat{\tau}^{DC}$ variables indicate the (active) change risky share at specific time intervals relative to DC plan enrollment. Standard errors clustered at the individual level are reported in parentheses.

Appendix A Details on Occupational Pension Collective Agreements

Understanding the structure and specifics of Sweden's occupational pension collective agreements is crucial for analyzing their impact on investment behavior and financial outcomes. This section synthesizes key information gathered from policy reports, academic research, and official agreement documentation (Calvet et al. (2023a), Hagen (2013), Hagen (2017), Jansson, Ottosson, Murhem, and Magnusson (2018), Sjögren Lindquist and Wadensjö (2006), Anderson (2015), Lindquist and Wadensjö (2009), Palme and Svensson (2004), Fora AB, Collectum AB, KPA Pension, Kåpan Pensioner). By providing an overview of these agreements for different worker groups—blue-collar, white-collar, central government, and local government employees—this section outlines the evolution, contribution structures, and investment choices available within the Swedish pension system.

Appendix A.1 Blue collar workers

Summary: Contributions begin accruing at age 28 up until 1999, at age 22 in 2000 and 2001, and at age 21 from 2002 onward.

Introduced in 1996, the SAF-LO contract pension is a defined contribution system. The employer contributes 3.5% of the employee's salary each year. (Avtalspension (2024)) All earnings are pensionable from the age of 21, with the pensionable age reduced from 28 to 22 in 2000 and to 21 in 2002. Employees may choose between two types of pension plans: traditional pension insurance, which offers a guaranteed minimum return, or mutual fund insurance.

Members also select their fund manager. Six traditional pension insurance companies and five companies offering unit-linked annuities are available for selection. For non-choosers, there is a default fund. Strict limits are imposed on the risk level any fund may take. The default fund is a fixed annuity provider, and about 65% to 70% of members are enrolled in the default fund.

Appendix A.2 White collar workers

Summary: Before 2007, contributions began accruing at age 28; after July 2007, contributions started at age 25.

Before 2007. The supplementary pension for white-collar workers in industry and trade, ITP, was introduced in 1960. The ITP plan included all white-collar workers in companies covered by

the agreement, except for managing directors in limited companies, and it had a defined benefit (DB) structure. ITP years were earned from the age of 28.

A DC component, called ITPK (where 'K' stands for supplementary), was introduced in 1977. Contributions to ITPK amounted to approximately 2 percent of each worker's earnings up to 30 base amounts (BAs). Prior to 1990, the ITPK plan operated as if each payment generated a benefit, with ITPK payouts being part of the collective refund, combining elements of both DB and DC schemes. In 1990, this changed, and it became possible to invest ITPK contributions in guaranteed or unit-linked products provided by companies such as Collectum or Valcentralen (Palme and Svensson (2004)).

In 1990, high earners (those earning more than 10 income-related base amounts (IBB) per month) could waive guaranteed ITP benefits above 7.5 IBB and set up their own DC plan, known as *Alternative ITP*. In this arrangement, the employer subscribes to another pension solution, often a fixed-premium "ten-tag solution". The details of this ten-tag solution, such as the amount the employer contributes, are not specified in the collective agreement and are left to the employer's discretion. Both the employer and employee must agree to opt for the employer's offer instead of the collective agreement's defined benefit ITP. Collectum reported that around half of eligible high-earners switched to Alternative ITP.

After 2007. The general transition of the ITP plan to a defined contribution system began in 2006, with a new plan taking effect on 1 July 2007. The new ITP plan consists of two sections: ITP1, a defined contribution retirement pension for civil servants born in 1979 or later. Employers contribute 4.5% of income up to the statutory ceiling and 30% of income above it.

Half of the contribution is allocated to fixed annuity products, with members selecting from four fund providers. For the other half, members choose between five providers offering fixed or unit-linked annuity products (Pensionsåldersutredningen (2012)). Non-choosers' contributions are placed in a default option, which is a lifetime fixed annuity with repayment protection.

The second section, ITP2, is a defined benefit retirement pension for civil servants born in 1978 or earlier. ITP2 continues the old ITP plan with some modifications. At retirement age 65, the compensation levels are as follows: 10% of salary up to 7.5 IBB, 65% of salary between 7.5 and 20 IBB, and 32.5% of salary between 20 and 30 IBB. Employers who signed ITP agreements before 25 April 2006 have their employees insured under both sections of the ITP plan. Employers contribute 2 percent of the pension base to individual accounts, and participants can choose how the funds

are invested. Participants may select between fixed and variable annuity products.

Appendix A.3 Central Government Workers

Summary: To be enrolled for a DC, an individual had to be at least 28 years of age until 2002, and at least 23 years old after 2003.

Prior to 1992, the occupational pension scheme for employees in the central government provided a gross pension, meaning that it fully replaced the state pension for workers covered by the scheme. After 1992, PA-91 pension scheme was introduced. The major part of the PA-91 pension was a DB scheme, where the occupational pension was based on the average of the last five annual salaries before the year of retirement. Additionally, there was a supplementary old-age pension financed by employers under PA-91, where contributions were made under the *Kåpan Tjänste* (1.7% of the employee's salary since 1995) and *Kåpan Extra* (introduced in 1998).

As of January 1, 2003, PA-91 was replaced by PA-03 (PA-91 payments continued after the introduction of PA-03 for individuals born before 1943). From age 23, central government employers began paying the *individuell ålderspension* premium. This pension is a DC scheme, where the employer finances this part of the pension by paying a fee for pension insurance. The premium corresponds to approximately 2.5% of the pension base, and employees can choose between fixed and unit-linked annuity products. There are nine providers of fixed annuities and thirteen providers of variable annuities, with each company offering between four and thirty-one funds. For non-choosers, the default fund is a lifelong fixed annuity.

Starting at age 28, employers also pay the *Kåpan* premium, which corresponds to 2% of the employee's salary or pension base up to an annual salary of 30 income base amounts. Employers transfer the *Kåpan* premiums to the Insurance Association for the state sector, *Kåpan Pensioner Försäkringsförening*, and the employee does not have the option to choose the management of this coverage.

Appendix A.4 Local Government Workers

Summary: enrollment eligibility age between 1998 and 2003 was at least 28 years old, and after 2004, the age was reduced to 21.

The new pension scheme for local government employees came into effect in 1998, around the

same time the new public pension scheme was implemented, serving as an adaptation to the new public pension system.

Initially, the pension scheme consisted solely of a contribution-based component. However, in 2000, an individual component was introduced, allowing employees to invest their pension in either a traditional pension insurance or a unit-linked insurance. By 2003, the contribution-based component was completely removed, and since then, the pension has only consisted of an individual component. Employees now have the freedom to choose among various fund managers and select the level of risk for their investments (Glans (2009)).

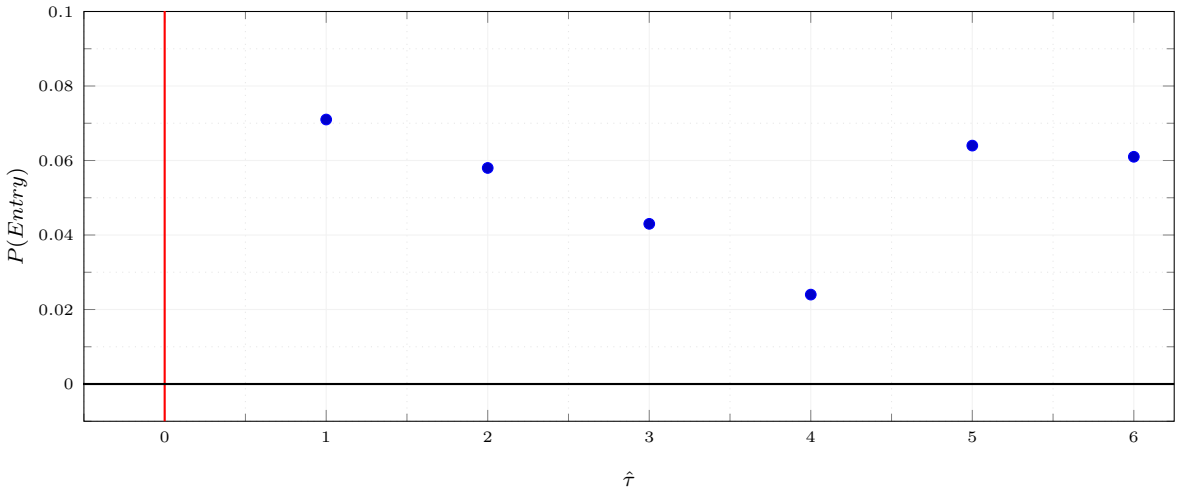
The contribution, paid by the employer, has varied slightly over time and depending on the employer, period, and tenure, but generally centered around 3.4–3.5% for wage portions below the income ceiling and 1–1.1% for earnings above the ceiling.

From 1998 to 2003, employees could credit an annual pension contribution to the contribution base starting at age 28. In 2004, the eligibility age was lowered from 28 to 21 years for the majority of employees in the contract area.

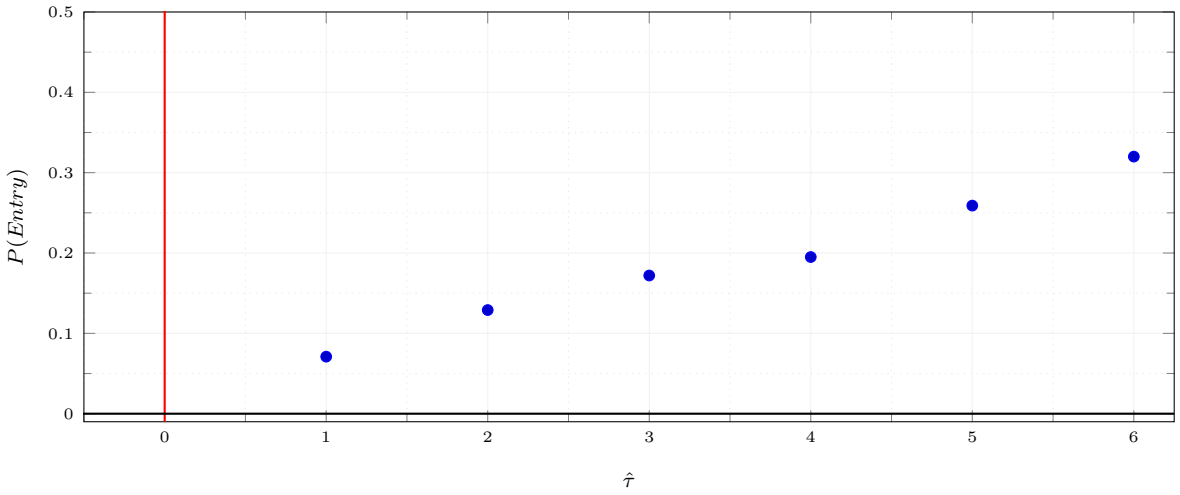
Three companies offer fixed annuities, and twelve companies offer unit-linked annuities. Participants can choose from between four and forty funds, depending on how many are offered by the selected company Ministries of Finance and Social Affairs (2013). For non-choosers, the default fund is a fixed annuity fund.

Appendix B Additional Descriptive Statistics

Figure A1: Unconditional Mean of Entry Probability: (a) Annual Change; (b) Cumulative effect



(a) Annual Change in Entry Probability



(b) Cumulative Change in Entry Probability

Figure A1 depicts the unconditional mean of stock market entry probability in the sample. The probabilities are calculated by identifying a sample of non-participants in a specific year and tracking their stock market participation over time (up to six years). An entry is recorded if an individual participated in the stock market at least once by year τ. Given the time-series dimension of the sample, I observe the evolution of entry probability over the full six-year period only for the 1999, 2000, and 2001 year groups. For subsequent year groups, the observation period is shorter. To compute the unconditional mean entry probability, I first calculate the series of probabilities for each year group and then average these probabilities across all year groups for each τ.

Appendix C Additional Empirical Results

In this section, I provide supplementary analyses to assess the robustness of our main findings. Specifically, I examine how an alternative approach of clustering standard errors affects the statistical significance of my results.

Appendix C.1 Alternative Clustering for Standard Errors

My baseline regressions cluster standard errors at the individual level to account for serial correlation in the error terms over time for each individual. However, unobserved shocks may also be correlated across individuals who are of the same age, reside in the same region, or work in the same occupation. The latter clustering group is more conservative than the former, thus, may lead to higher standard errors.[45] To address this concern, I re-estimate my main models using alternative clustering methods.

Table A1 presents the regression results for stock market entry and DC plan eligibility with standard errors clustered at the age-year-region-occupation level. The key coefficient of interest, representing the effect of DC plan enrollment on stock market entry in the first year of treatment, remains positive and statistically significant in the specifications (2) and (3).

Similarly, Table A2 shows the regression results for the change in risky share and DC plan enrollment, also with standard errors clustered at the age-year-region-occupation level. The positive and significant coefficients confirm that individuals enrolled in DC plans tend to increase their allocation to risky assets in their non-pension portfolios. This effect holds for both the overall change in risky share and the active change in risky share, reinforcing my earlier conclusions.

Lastly, Tables A3 and A4 provide regression results from the Health and Retirement Study (HRS) data for the U.S., with standard errors clustered at the age-year level. The findings remain consistent with those from the Swedish data, suggesting that the positive impact of DC plan enrollment on stock market entry and risky share is robust to alternative clustering methods.

Overall, these additional results confirm that my main findings are not sensitive to the way standard errors are clustered. The statistical significance and economic magnitude of the estimated effects persist under different clustering assumptions, further supporting the causal relationship between DC plan enrollment and individuals' non-pension investment behavior.

[45] See a comprehensive discussion on standard error clustering in Abadie, Athey, Imbens, and Wooldridge (2023).

Table A1: Regression result for Stock Market Entry and DC plan Eligibility with Alternative SEs.

	(1)	(2)	(3)
$\hat{\tau}^{DC} = 1$	0.002	0.003*	0.003*
	(0.002)	(0.002)	(0.001)
$\Delta \log FW_t$	0.056***	0.055***	0.056***
	(0.001)	(0.001)	(0.001)
$\log Y_t$	0.041***	0.038***	0.037***
	(0.001)	(0.001)	(0.001)
Occupation (Base is White collar)			
Central Gov	-0.030***	-0.029***	-0.029***
	(0.002)	(0.002)	(0.002)
Local Gov	-0.044***	-0.040***	-0.042***
	(0.001)	(0.001)	(0.001)
Blue Collar	-0.031***	-0.029***	-0.031***
	(0.001)	(0.001)	(0.001)
Education (Base is no high school)			
High School	0.017***	0.015***	0.015***
	(0.001)	(0.001)	(0.001)
Some College	0.029***	0.025***	0.025***
	(0.001)	(0.001)	(0.001)
Graduated College	0.053***	0.047***	0.047***
	(0.001)	(0.001)	(0.001)
Post-Grad	0.041***	0.037***	0.038***
	(0.005)	(0.005)	(0.005)
Marriage status (Base is not married)			
Married		-0.019***	-0.019***
		(0.001)	(0.001)
Divorced		-0.022***	-0.021***
		(0.002)	(0.002)
Widowed		0.014	0.015
		(0.024)	(0.024)
Have kids		-0.015***	-0.015***
		(0.001)	(0.001)
Owner		0.012***	0.012***
		(0.000)	(0.000)
Year and Age FE	Yes	Yes	Yes
Region FE	No	No	Yes
Pseudo R2	0.147	0.150	0.151
N	1,504,753	1,504,753	1,504,753

Standard errors clustered at age-year-region-occupation level in parentheses
Estimates are ME evaluated at sample averages
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2 presents the estimation results for the dynamic effects from regression equation (10) estimated using Probit model: $P(Entry_{it}) = \alpha + \sum_{j=-3}^{-1} \beta_j I[_{\hat{\tau}^{DC}=j}] + \beta_1 I[_{\hat{\tau}^{DC}=1}] + \sum_{j=2}^{6} \beta_j I[_{\hat{\tau}^{DC}=j}] + \theta X_{it} + I[a_{it}] + I[y_t] + \varepsilon_{it}$, where the dependent variable is the probability of stock market entry $P(Entry_{it})$, so I estimate the regression conditional on no stock market participation in previous period. The independent variables include indicators for time relative to DC plan enrollment ($\hat{\tau}^{DC} = j$), life-cycle controls X_{it}, age fixed effects $I[a_{it}]$, and year fixed effects $I[y_t]$. Columns (1), (2) and (3) show specifications with different sets of controls, progressively adding covariates such as occupation, education, marital status, ownership status, region of residentship. All specifications in this table control for log-change in wealth ($\Delta \log FW_t$) and log income ($\log Y_t$). I only report the treatment effect in the first year of treatment (coefficient β_1), while the full set of dynamic effects is shown in Figure 4. The table shows the marginal effects evaluated at sample averages. Standard errors are clustered at age-year-region-occupation level.

Table A2: Regression Result for Risky Share and DC Plan enrollment with Alternative SEs.

	(1) Δw_t	(2) Δw_t^{active}
$\hat{\tau}^{DC} = 1$	0.006**	0.004*
	(0.001)	(0.002)
$\log FW_{t-1}$	0.016***	0.018***
	(0.001)	(0.001)
$\log Y_t$	0.000***	0.000***
	(0.000)	(0.000)
Occupation (Base is White collar)		
Central Gov	0.004***	0.001
	(0.001)	(0.001)
White Collar	-0.005***	0.005***
	(0.002)	(0.002)
Blue Collar	-0.002	-0.001
	(0.001)	(0.001)
Education (Base is no high school)		
High School	-0.006***	-0.005***
	(0.001)	(0.001)
Some College	-0.005***	-0.000
	(0.001)	(0.001)
Graduated College	-0.015***	-0.012***
	(0.001)	(0.001)
Post-Grad	-0.015***	-0.012***
	(0.003)	(0.004)
Marriage status (Base is not married)		
Married	-0.000	0.001*
	(0.001)	(0.001)
Divorced	0.009**	0.006
	(0.004)	(0.004)
Widowed	0.039	0.014
	(0.035)	(0.035)
Have kids	0.008***	0.008***
	(0.001)	(0.001)
Owner	-0.008***	-0.005***
	(0.001)	(0.001)
Year and Age FE	Yes	Yes
Region FE	Yes	Yes
Adj. R2	0.0551	0.0341
N	1,666,819	1,666,819

Standard errors clustered at age-year-region-occupation level in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3 presents the estimation results for the dynamic effects from regression equation (11) estimated for the subsample of stock market participants in both previous and current period: $\Delta\omega_{it}^{(a)} = \alpha + \sum_{j=-3}^{-1} \beta_j I[\hat{\tau}^{DC}=j] + \beta_1 I[\hat{\tau}^{DC}=1] + \sum_{j=2}^{6} \beta_j I[\hat{\tau}^{DC}=j] + \theta X_{it} + I[a_{it}] + I[y_t] + \varepsilon_{it}$, where the dependent variable is the (active) change in risky share $\Delta\omega^(a)_{it}$ of individual i at time t. The independent variables include indicators for time relative to DC plan enrollment ($\hat{\tau}^{DC} = j$), life-cycle controls X_{it}, age fixed effects $I[a_{it}]$, and year fixed effects $I[y_t]$. Column (1) shows the result of the change in risky share ($\Delta\omega_{it}$), and column (2) shows the estimations for the active change in risky share ($\Delta\omega_{it}^a$). Both regressions include the full set of covariates (wealth and income controls, occupation, education, marital status, and ownership status). I only report the treatment effect in the first year of treatment (coefficient β_1), while the full set of dynamic effects is shown in Figure 5. The table shows the marginal effects evaluated at sample averages. Standard errors are clustered at age-year-region-occupation level.

Table A3: Regression results for DC Pension Plan effect on Stock Market Entry with Alternative SEs.

	Baseline	IRA Control
	(1)	(2)
$\hat{\tau}^{DC} = -4$	0.004	-0.008
	(0.023)	(0.024)
$\hat{\tau}^{DC} = -2$	0.003	-0.003
	(0.020)	(0.020)
$\hat{\tau}^{DC} = 2$	0.002	-0.002
	(0.013)	(0.013)
$\hat{\tau}^{DC} = 4$	0.032***	0.021*
	(0.012)	(0.012)
$\hat{\tau}^{DC} = 6$	0.006	-0.003
	(0.014)	(0.014)
$\hat{\tau}^{DC} = 8$	0.028*	0.018
	(0.017)	(0.017)
	(0.016)	(0.016)
$\hat{\tau}^{DC} = 10$	0.082***	0.067***
	(0.019)	(0.019)
$\hat{\tau}^{DC} = 12$	0.032***	0.023***
	(0.007)	(0.008)
$\Delta \log FW_t$	0.079***	0.079***
	(0.002)	(0.002)
IRA		0.077***
		(0.006)
Life Cycle Controls	Yes	Yes
Preference Controls	Yes	Yes
Year and Regions FE	Yes	Yes
N	17,370	16,862

Standard errors clustered at age-year level in parentheses
Marginal effects evaluated at sample averages
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A3 presents the regression results for the Equation 15: $P(Entry_{it}) = \alpha + \sum_{j=-4}^{-2} \beta_j I[_{\hat{\tau}^{DC}=j}] + \beta_1 I[_{\hat{\tau}^{DC}=1}] + \sum_{j=4}^{12} \beta_j I[_{\hat{\tau}^{DC}=j}] + \theta X_{it} + I[a_{it}] + I[y_t] + \varepsilon_{it}$ assessing the effect of DC pension plan enrollment on the probability of stock market entry in the HRS data for the US. Sample includes only individuals who did not participate in the stock market in the previous period, so the dependent variable $P(Entry_{it})$ is a binary indicator of whether an individual enters the stock market. The key independent variables are time indicators relative to DC plan enrollment, denoted by $\hat{\tau}^{DC} = j$, where j represents years before ($j < 0$) or after ($j > 0$) DC enrollment. Column (1) shows the baseline specification, while Column (2) includes an additional control for IRA ownership. Models incorporate life cycle controls, preference controls, and fixed effects for year and region. The coefficients for $\hat{\tau}^{DC}$ variables indicate the change in the probability of stock market entry at specific time intervals relative to DC plan enrollment. The reported effects are marginal effects are evaluated at the sample averages. Standard errors clustered at the age-year level are reported in parentheses.

Table A4: Regression results for DC Pension Plan effect on Risky Share with Alternative SEs.

	$\Delta\omega$		$\Delta\omega^a$	
	(1)	(2)	(3)	(4)
$\hat{\tau}^{DC} = -4$	0.009	0.008	0.008	0.007
	(0.039)	(0.040)	(0.039)	(0.040)
$\hat{\tau}^{DC} = -2$	0.040	0.039	0.038	0.037
	(0.028)	(0.028)	(0.027)	(0.028)
$\hat{\tau}^{DC} = 2$	0.006	0.005	0.005	0.004
	(0.021)	(0.021)	(0.021)	(0.021)
$\hat{\tau}^{DC} = 4$	-0.006	-0.007	-0.006	-0.007
	(0.016)	(0.016)	(0.016)	(0.016)
$\hat{\tau}^{DC} = 6$	0.025	0.024	0.023	0.022
	(0.024)	(0.024)	(0.023)	(0.023)
$\hat{\tau}^{DC} = 8$	0.009	0.008	0.009	0.008
	(0.020)	(0.020)	(0.021)	(0.021)
$\hat{\tau}^{DC} = 10$	0.032	0.031	0.031	0.031
	(0.031)	(0.032)	(0.030)	(0.030)
$\hat{\tau}^{DC} = 12$	0.001	0.000	0.001	0.000
	(0.013)	(0.013)	(0.012)	(0.012)
$\Delta \log FW_t$	0.079***	0.079***	0.079***	0.079***
	(0.006)	(0.006)	(0.006)	(0.006)
IRA		0.009		0.009
		(0.009)		(0.009)
Life Cycle Controls	Yes	Yes	Yes	Yes
Preference Controls	Yes	Yes	Yes	Yes
Year and Regions FE	Yes	Yes	Yes	Yes
N	8,379	8,379	8,379	8,379

Standard errors clustered at age-year level in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A4 presents the regression results for the Equation 16: $\Delta\omega_{it}^{(a)} = \alpha + \sum_{j=-4}^{-2} \beta_j I[\hat{\tau}^{DC}=j] + \beta_1 I[\hat{\tau}^{DC}=1] + \sum_{j=4}^{12} \beta_j I[\hat{\tau}^{DC}=j] + \theta X_{it} + I[a_{it}] + I[y_t] + \varepsilon_{it}$ assessing the effect of DC pension plan enrollment on the change in (active) risky share for stock market participants in the HRS data for the US. Sample includes only individuals who participate in the stock market in the previous and current period. The key independent variables are time indicators relative to DC plan enrollment, denoted by $\hat{\tau}^{DC} = j$, where j represents years before ($j < 0$) or after ($j > 0$) DC enrollment. Column (1) shows the baseline specification, while Column (2) includes an additional control for IRA ownership for the change in risky share. Columns (3) and (4) present the results for the active change in risky share, accordingly. Models incorporate life cycle controls, preference controls, and fixed effects for year and region. The coefficients for $\hat{\tau}^{DC}$ variables indicate the (active) change risky share at specific time intervals relative to DC plan enrollment. Standard errors clustered at the age-year level are reported in parentheses.