Graduate Institute of International and Development Studies

International Economics Department

Working Paper Series

Working Paper No. HEIDWP01-2023

Do pension funds reach for yield? Evidence from a new database

Maximilian Konradt
Graduate Institute of International and Development Studies, Geneva

Chemin Eugène-Rigot 2
P.O. Box 136
CH - 1211 Geneva 21
Switzerland

Do pension funds reach for yield? Evidence from a new database

Maximilian Konradt*

Geneva Graduate Institute

This version: February 1st, 2023§

Abstract

This paper investigates the financial risk-taking behavior of pension funds since 2000. I assemble a new database containing portfolio holdings of more than 100 pension funds from 14 advanced economies. The study reveals three key findings. First, I show that pension fund portfolios have become riskier over that period, with an average increase in risky asset weights of 4 percentage points since 2008. European pension funds tend to invest more in public equities, while North American and Asian funds focus on alternative assets. Second, I find evidence that declining domestic risk-free rates play a significant role in driving the trend, with pension funds increasing their risky asset exposure in response to falling short-term interest rates. Third, I demonstrate that less underfunded pension funds with fewer risky assets tend to reach for yield more aggressively, which is exacerbated during periods of low risk-free rates. This is most pronounced for European pension funds, particularly after the global financial crisis.

JEL classification codes: E43, F21, G11, G23

Keywords: Low interest rates, Pension funds, Risk-taking, Reach for yield

*Geneva Graduate Institute, Chem. Eugène-Rigot 2, 1202 Genève. Phone +41 778 154 852. E-mail: maximilian.konradt@graduateinstitute.ch.

§I am grateful to my advisors Cédric Tille and Beatrice Weder di Mauro for guidance and support. I also thank Aleksandar Andonov, Harald Hau, Victoria Ivashina, Pab Jotikasthira, Ricardo Reis, Nathan Sussman, Yannick Timmer, Christoph Trebesch and Andrei Zlate, as well as seminar participants at the 2022 Midwest Macro Meeting, Geneva Graduate Institute, University of Lausanne, the 30th CEPAR Colloquium on Pensions and Retirement Research and the 2022 SSES Congress for helpful comments and discussions. This project has benefited from financial support by the Swiss National Science Foundation (grant 203892).

1 Introduction

With the trend of increasing interest rates in advanced economies, it is crucial to understand the consequences of the prolonged low interest rate environment on financial institutions. Specifically, did low interest rates drive investors to reach for yield, by shifting towards riskier assets (e.g., Rajan 2006, Stein 2013, IMF 2019)? These concerns are of particular significance for pension funds, as they must align their portfolios with the long-term structure of their liabilities.

This paper studies pension funds' balance sheets during the time of low interest rates. I ask how pension funds adjust their exposure to risky assets, relative to their total asset holdings, in response to falling interest rates. To address this question, I assemble a comprehensive international database of pension funds' financial investments.

Examining shifts in pension funds' balance sheets during the low interest rate period is essential to uncover potential risks associated with rising interest rates. In particular, pension funds' increased exposure to riskier assets may put their liquidity at risk during market disruptions. This was underscored in 2022, when UK pension funds were forced to liquidate significant bond holdings in response to margin calls.[1] The episode reinforces the importance of thoroughly evaluating pension funds' balance sheet resilience, and to what extent it has been impacted by the prolonged low interest rates.

Despite pension funds' more stable funding structure compared to other types of investors, their balance sheets are not immune to changes in interest rates. For instance, pension funds often have long-term return targets that encourage them to move to higher yield assets in response to decreasing interest rates (see e.g., Bergstresser, Desai, and Rauh 2006). In addition, Andonov and Rauh (2022) demonstrate that return expectations are commonly based on previous experiences and tend to persist over time.

Despite their systemic size and importance in facilitating inter-generational risk-sharing (e.g., Merton 1983), studies on pension funds' investment behavior are scarce compared to other types of investors, due to the limited availability of granular data (e.g., Antolin 2008, Andonov, Bauer, and Cremers 2012).[2] Systematically

[1] After announcing a new fiscal policy, UK bond yields decreased rapidly, which led to margin calls on derivative contracts to match the long-term duration of pension funds' liabilities. Pension funds selling off bonds further exacerbated the price pressure, which forced the Bank of England to intervene through asset purchases. For more details, see https://www.bloomberg.com/news/articles/2022-10-14/ninety-one-ceo-says-uk-pensions-crisis-exposes-structural-holes.

[2] The OECD (2019) estimates that pension funds in member countries manage assets worth 32 trillion US dollars as of 2019, accounting for 65% of GDP. In a similar scan of the pension fund industry, Willis Tower Watson (2019) reports positions of 44.1 trillion US dollars globally in 2018,

collected data of individual funds over a long time span is scarce non-existent for many countries, outside of the US (see e.g., Mohan and Zhang 2014). This paper tries to fill this gap by putting together a database covering more than 100 funds from 14 advanced economies over a 20-year period. In 2018 it encompasses aggregate asset positions of 8.4 trillion US dollars.

In a purely descriptive exercise, I start by presenting stylized facts on pension funds' balance sheets over the past 10 years. The average fund in the sample has increased its allocation to risky assets, such as public equities, loans, and alternative investments, by 4.3 percentage points over the past decade. Using geographical variation, I observe that funds based in Europe are more likely to invest in public equities, while funds from North America and Asia tend to allocate more towards alternative assets.

Next, I perform an econometric analysis of the funds' investment behavior in response to changes in domestic short-term interest rates. The results of this analysis explain the growth in pension funds' risky asset holdings.

First, the trend towards more risk-taking can at least in part be attributed to reach for yield, meaning that funds buy riskier, high-yield assets when interest rates decrease. In the baseline empirical specification, after controlling for changes in the risk-premium and including fund and year fixed effects, I estimate that a 1 percentage point fall in the domestic risk-free rate is associated with a 0.66 percentage point increase in a funds' risky asset share. Importantly, the increase in risk-taking only reflects net purchases and is not influenced by valuation effects. The finding is consistent with previous research on a narrower sample of US pension funds (e.g., Chodorow-Reich 2014).

Pension fund investments can drive bond prices, particularly for longer maturities (see Greenwood and Vissing-Jorgensen 2018). To isolate the unanticipated, exogenous changes in interest rates, I use an instrumental variables approach and monetary policy shock (e.g., Nakamura and Steinsson 2018, Jarociński and Karadi 2020), with comparable results. Moreover, I test alternative proxies for the risk-free rates and risk-premia. The main findings also remain unchanged controlling for potential confounding factors related to demographics, regulation, and central bank asset purchases.

Second, I explore heterogeneity across funds in funds' tendency to reach for yield. The results suggest that funds with excess capacity, that are comparatively less underfunded and holding fewer risky assets on their balance sheets, reach for yield more aggressively. Moreover, reach for yield is exacerbated at lower levels of domestic

with more than 80% held by pension funds in the seven biggest markets.

short-term interest rates.

Third, I draw on geographical variation to assess differences in pension funds' investment behavior. Specifically, I differentiate between pension funds located within and outside Europe, which are exposed to distinct macro-financial conditions. Adopting the same empirical framework, the findings indicate that European pension funds are more inclined to reach for yield more aggressively compared to their foreign peers. This is particularly evident in the aftermath of the 2008 financial crisis, when European funds were facing lower risk-free rates and had greater risk-taking capacity relative to North American and Asian funds. Importantly, this result comes against the backdrop of a higher *level* of risky assets by Non-European funds, as discussed below.

The finding that pension funds strategically reach for yield in response to changing risk-free rates has important implications for evaluating the consequences of monetary policy and for designing macro-prudential regulation. It is consistent with earlier research on other types of financial institutions.

Related Literature. This paper ties into several strands of previous literature. First, it contributes to literature focusing on the consequences of low interest rates on financial market participants, specifically on risk-taking. Previous studies show that banks (e.g., Ioannidou, Ongena, and Peydró 2015, Maddaloni and Peydró 2011, Heider, Saidi, and Schepens 2019), mutual funds and money market funds (e.g., Choi and Kronlund 2018, Hau and Lai 2016, Di Maggio and Kacperczyk 2017) increase their investments in riskier assets in response to falling interest rates. Ammer et al. (2019) document the same pattern in moderately aggregated data across investors. The present study documents that reach for yield also spans to an international sample of pension funds.

A smaller body of research has studied the effects of low interest rate policy on long-term investors, such as insurance companies and pension funds. On the former, Becker and Ivashina (2015) and Ozdagli and Wang (2019) document reach for yield within the fixed income portfolios of insurers. For the latter group of pension funds, Andonov, Bauer, and Cremers (2017) find that US public pension plans hold more risky assets compared to their private and European counterparts. Chodorow-Reich (2014) and Lu et al. (2019) show reach for yield in a sample of private and public US pension funds, respectively. In the same vein, Ivashina and Lerner (2018) find that funds domiciled in countries with lower interest rates shift more towards alternative investments over the past decade. This paper builds on the previous studies by showing that reach for yield by pension funds extends beyond

US borders and specifically sheds light on funds based in Europe.[3]

My empirical result of reach for yield is consistent with model-based studies that assess the consequences of low interest rates on long-term investors. For instance, Domanski, Shin, and Sushko (2017) suggest that institutional investors are induced to take more financial risk when facing a tightening mismatch between assets and liabilities as a result of low interest rates. Campbell and Sigalov (2022) use a sustainable spending constraint which ties the consumption of a wealth manager to its expected rate of return and promotes reach for yield. Lian, Ma, and Wang (2019) explain the greater propensity to take risk when interest rates are low in a behavioral framework.

More broadly, the present paper relates to a literature focusing on investors' portfolio allocation and rebalancing behavior over the financial cycle (e.g., Bohn and Tesar 1996, Brennan and Cao 1997, Calvet, Campbell, and Sodini 2009, Camanho, Hau, and Rey 2022). For pension funds and insurance companies, Timmer (2018) shows that German investors display counter-cyclical behavior, i.e. selling (buying) bonds after their price has increased (decreased). Another set of studies find evidence of pro-cyclical behavior (e.g., Ellul et al. 2021, Rousová and Giuzio 2019, Bergant and Schmitz 2019), albeit based on different samples. My empirical findings are consistent with the former view: pension funds reduce their exposure to risky assets when the risk premium increases, and vice versa.

Finally, the paper contributes to the general literature on pension funds' investment behavior by assembling a novel international database. Due to data limitations, the lion share of the previous research is based US public pension funds (e.g., Novy-Marx and Rauh 2009, Novy-Marx and Rauh 2011, Mohan and Zhang 2014). Outside of the US public funds, there are individual country case studies (e.g., Bikker, Broeders, and De Dreu (2010) for Dutch pension plans, Autrup and Jensen (2021) for Danish pension funds, Rauh (2009) for US private funds). As a result, cross-country analyses of pension funds are scarce by comparison (e.g., French 2008, Andonov, Bauer, and Cremers 2017) and mainly explore cross-sectional variation due to limited coverage. The database I put forth in this paper will permit future research to build on a broad set of funds from different countries. Importantly, the long time span and consistency of reporting also allows dynamic inference.

The remainder of the paper is organized as follows. In the next section, I introduce the database on pension fund investments and provide first stylized facts on the composition of pension funds' balance sheets over time. The conceptual framework

[3] Lu et al. (2019) and Chodorow-Reich (2014) focus only on US pension plans while the sample in Andonov, Bauer, and Cremers (2017) favors US pension funds and has limited coverage in Europe.

for studying the response of pension funds' risk-taking to interest rate changes is laid out in Section 3. Section 4 guides through the empirical strategy to identify the effect of interest rates on pension fund investment behavior. The various set of results related to reach for yield and heterogeneous effects over time and across funds are contained in Section 5. Finally, Section 6 concludes.

2 A new database on pension fund investments

One of the main challenges in analyzing pension funds and their investment behavior across countries is the scarcity of sufficiently granular data.[4] I attempt to bridge this gap by collecting data to construct a comprehensive international database of pension funds' asset holdings. This section summarizes the main variables in the database and highlights general investment patterns and risk-taking behavior of pension funds. Appendix B contains a more detailed description of how the data are assembled, as well as information on coverage and included funds.

2.1 Description and Summary Statistics

The new database offers a comprehensive view of the pension fund sector, encompassing funds from 14 advanced economies across three continents. It comprises more than 100 large, mostly public defined benefit pension funds and is extensive in scope: as of 2018, the database include pension fund assets worth 8.4 trillion US dollars, making up over one third of the total assets held by defined benefit pension funds globally.[5] Represented as a share of national GDP, the assets held by pension funds account for 43% per country on average.

The pension funds in the data are mostly identified using the Global Top 300 pension fund ranking by Willis Tower Watson (WTW), which is published annually.[6] I obtain the data from annual reports and financial statements that pension funds publish at the end of each accounting year.[7] I only include a pension fund in the

[4]Notable exceptions include the Public Plans Database for public (e.g., Mohan and Zhang 2014), and the CEM database for private and public pension funds (e.g., French 2008; Andonov, Bauer, and Cremers 2017). While the former database spans only US public pension plans, the latter favors mainly US and Canadian plans, has only limited coverage for Europe and does not allow to study pension fund behavior over a longer time span. An additional drawback of the CEM data is that fund location is anonymized, complicating cross-country studies.

[5]Willis Tower Watson (2019) estimates that of the 44.1 tn. US dollars of global investments, about half are in defined benefit pension plans.

[6]See https://www.thinkingaheadinstitute.org/the-worlds-largest-pension-funds-2020/.

[7]Recently, there has been an increase in the use of publicly disclosed financial data for academic purposes, see e.g. Hassan et al. (2019) for earnings call transcripts, Handley and Li (2020) for SEC filings.

database if its annual reports have been available for at least ten years.

Along with standard balance sheet information, the annual reports provide extensive information on asset portfolios, including the weights of different asset classes in the portfolios and the annual returns within each asset class. Additionally, many funds report on their funding status, discount rates, and composition of retirees. Further details on the data extraction and cleaning procedures are provided in Appendix B.

To the best of my knowledge, the present database is among the most comprehensive in the literature. To date, empirical research on pension funds primarily uses the US Public Plans or the CEM database. The former includes holdings of 4.3 trillion US dollars (in 2018) and is restricted to US funds. The latter covers international fund holdings of 10.1 trillion US dollars at the end of 2018, but has limited information on fund origin and suffers from inconsistent reporting over time. In a recent paper, Ivashina and Lerner (2018) use data from Preqin, which captures 19.7 trillion US dollars as of 2017. The drawback of the dataset is the short coverage and incomplete information for other asset classes.

Importantly, the database in this paper covers a 20-year period, from 2000 to 2020, during which global pension fund assets more than tripled, growing from 16.3 to 52.5 trillion US dollars, as reported by Willis Tower Watson (2021). The database's coverage is limited by irregular reporting in its early years. From 2008 on, the panel is balanced and experiences very little sample attrition. Appendix B contains further information on the sample

Table 1 provides a breakdown of the coverage by country. The majority of funds are located in the United States, reflecting the US's dominant pension fund-based retirement system, which is home to some of the largest funds globally. Additionally, pension funds from Canada, the UK and other European countries are well represented in the sample. The data only encompass three large Asian pension funds from Japan and South Korea.

Measured by the number of observations, roughly 35% of the sample consists of US funds, 10% are based in Canada, and the remaining half are located in Europe. Based on total assets, US-based funds account for a quarter of the holdings, a similar amount is held by Asian pension funds, and the remaining is held by Canadian (10%) and European (40%) pension funds, respectively.

Column 5 of Table 1 benchmarks the total holdings by country with aggregate data from the WTW Global Pension Asset Study (2018). Overall, the combined holdings in the database represent a quarter of the total pension fund assets reported in the 14 countries, varying between 10% in the US and 72% in South Korea.

Table 1: Sample coverage

Country	Funds	N	Assets (2018)	Coverage (2018)
Canada	10	203	916	59
Denmark	7	138	219	60
Finland	3	62	116	52
France	3	49	90	61
Germany	7	108	209	40
Italy	2	33	24	13
Japan	2	19	1,669	57
Netherlands	7	119	787	55
Norway	2	43	927	
South Korea	1	19	503	72
Sweden	5	97	202	59
Switzerland	7	126	178	21
United States	38	740	2,269	10
United Kingdom	12	225	300	11
	105	2,017	8,410	24

Notes: This table shows the sample coverage of the database by country of origin. Funds indicates the number of funds included, N denotes the number of fund–year observations, by country over the entire sample period. Assets (2018) aggregates the total holdings, denoted in billion US dollars. Coverage gives the share of assets (in %) in the database relative to the benchmark aggregate holdings reported in the WTW Global Pension Assets Study 2018. Figures for Denmark and Sweden are obtained from the WTW Top300 survey, for Norway they are missing.

The database has a significant advantage in its level of detail, with a wide range of variables on investment positions and financial returns by asset class, as well as other fund-level variables. This, combined with a cross-country dimension, allows for an analysis of the investment behavior of pension funds in international comparison.

The financial data listed in Table 2 provide a comprehensive view on pension fund portfolios, including opening and closing positions, and rates of return per year. I separately summarize the main variables of the database for the pooled sample including all pension funds (columns 1-3), as well as for European (columns 5-7) and Non-European pension funds (columns 8-10), respectively. All variables are recorded at the end of a funds' fiscal year. Beginning with the pension fund size (fair value of plan assets), the average fund holds almost 60 billion US dollars (with a median of 25.8 billion) in total assets, although European funds tend to be smaller compared to non-European funds.

Importantly, the portfolio data are dis-aggregated by asset classes, which permits to study changes in balance sheet composition over time due to returns and portfolio decisions. The asset classes include cash and equivalents, government and corporate bonds, loans, public equity, private equity, and alternative investments, which I define as real estate, infrastructure and commodities. Positions are reported before allocating the effects of derivatives, as is typical with portfolio data.

The second row of Table 2 reports on the share of risky assets in funds' portfolios. I adopt the definition of Andonov, Bauer, and Cremers (2017) to classify equity, alternative investments and loans as risky and cash and government bond holdings as safe assets. Pooled investment vehicles that can not be classified are excluded. On average, a fund allocates 58% of its assets towards risky assets, primarily in public equities (row 3). Alternative assets comprise another 12% of the average pension funds' holdings. Contrasting pension funds from different regions, we see European funds holding more than 20 percentage points fewer risky assets on their balance sheet compared to their foreign counterparts. Safe assets (row 4) make up about a third of the average pension fund's balance sheet.

I compute rates of return separately for the total, safe and risky portfolios, based on the asset class-specific returns. The average fund earns an annual return of 5.12%, driven by the 6.29% return of the risky portfolio, compared to 3% for the safe portfolio. On average, non-European pension funds earn a rate of return that is 1.5 percentage points higher than their European peers, on the order of magnitude of 1.5 percentage points, on average. This holds both for the risky and safe portfolio.

Additional fund characteristics include the funding status, relating a funds' discounted pension obligations to the fair value of of assets, and the corresponding discount rate. If not reported directly, I compute the funding status manually. The average pension fund's funding status is 105% (median 92%), based on a discount rate of 7.8%. Discount rates to value liablities tend to be higher in non-European countries (e.g., Andonov, Bauer, and Cremers 2017).[8] Despite discounting liabilities more, non-European funds are more underfunded in comparison to their European counterparts.

The database also encompasses data on demographic variables and income flows. The former includes the number of retirees and the active contributing members of the pension plan. The latter reports net employee and employer contributions, after accounting for pension payments to retirees. Funds earn capital income in the form of dividends and interest payments on their assets. Public funds periodically receive one-time transfers from municipal or local government entities as starting capital. The proportion of retired members is similar across geographical regions and inflows represent an an equal share of the total balance sheet, on average.

I supplement the core dataset with a set of macro-financial variables at the

[8]For US funds I use the reported GASB funding ratios, which should be seen as upper bounds of the actual funding ratios based on risk-free rates (see e.g. Novy-Marx and Rauh 2009).

Table 2: Descriptive statistics

	Pooled			European			Non-European		
	Mean	p50	SD	Mean	p50	SD	Mean	p50	SD
Total assets	58.85	25.78	133.62	42.35	19.38	99.07	75.20	33.95	159.06
Risky share	58.48	62.71	18.58	49.38	49.35	18.23	67.44	70.84	14.00
Equity share	43.63	43.89	15.86	38.17	37.72	16.40	49.01	50.26	13.28
Alternative share	12.76	9.11	11.82	7.40	6.44	6.83	18.03	16.36	13.24
Safe share	32.23	29.19	17.33	36.41	34.04	20.62	27.81	25.43	11.63
r_{it}^T	5.12	5.47	9.57	4.35	4.70	10.34	5.88	6.30	8.70
r_{it}^R	6.29	7.01	14.52	5.89	6.94	16.09	6.68	7.26	12.83
r_{it}^S	3.05	2.79	5.62	1.92	1.94	6.43	4.14	4.10	4.45
Funding status	105.41	91.95	83.44	119.48	99.8	104.68	94.72	87.10	60.61
Discount rate	4.78	4.60	2.03	4.06	4.00	2.01	5.40	5.60	1.83
Retired share	43.97	44.04	15.61	43.91	43.97	17.19	44.01	44.15	14.48
Net inflows	5.16	2.99	7.04	3.95	1.53	7.43	6.28	7.12	6.47

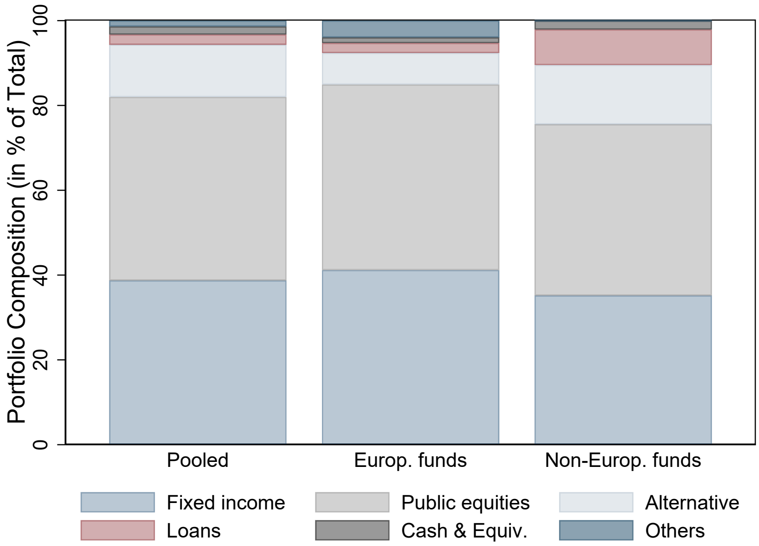
Notes: This table shows summary statistics of the main variables, for the pooled, the European and non-European pension funds, respectively. All variables are extracted at the end of a funds' fiscal year. Total assets denotes the balance sheet size expressed in billion US dollars. Risky and Safe give the percentage share of risky and safe assets to total assets on the balance sheet, where government bonds and cash holdings are classified safe, and the remaining assets are considered risky. r_{it}^T, r_{it}^R and r_{it}^S denote the fund-specific rates of return on the total, risky and safe portfolio. Discount rate, retired share and funding status are fund-specific variables, measuring the rate at which liabilities are discounted, the share of retired to total fund member and the ratio of assets to discounted liabilities, respectively.

country level. First, to proxy the risk-free rate I use 3-month interbank and 10-year government bond rates from the OECD, monetary policy rates retrieved from the BIS and shadow rates by Wu and Xia (2016). I use monetary policy shocks for the US and Euro area from Nakamura and Steinsson (2018), Altavilla et al. (2019) and Jarociński and Karadi (2020), respectively. Second, I include data on life expectancy at birth from the World Bank to account for demographic trends. I use data from the Annual Survey of Investment Regulation of Pension Funds by the OECD to proxy for regulatory changes.

2.2 Stylized facts on pension funds' portfolios

In this section I present stylized facts on pension funds' portfolios and the riskiness of their balance sheets. I start with Figure 1, which illustrates the portfolio composition of the average pension fund in the pooled, European and non-European sample, respectively. The average pension funds holds around 40% of fixed income assets, such as sovereign and corporate bonds, and 45% of public equity. Alternative, primarily private equity and real estate, account for 10%. The remaining 5% consists of loans, cash and "other" investments, mainly pooled investment vehicles than can not be classified.

Figure 1: Portfolio composition



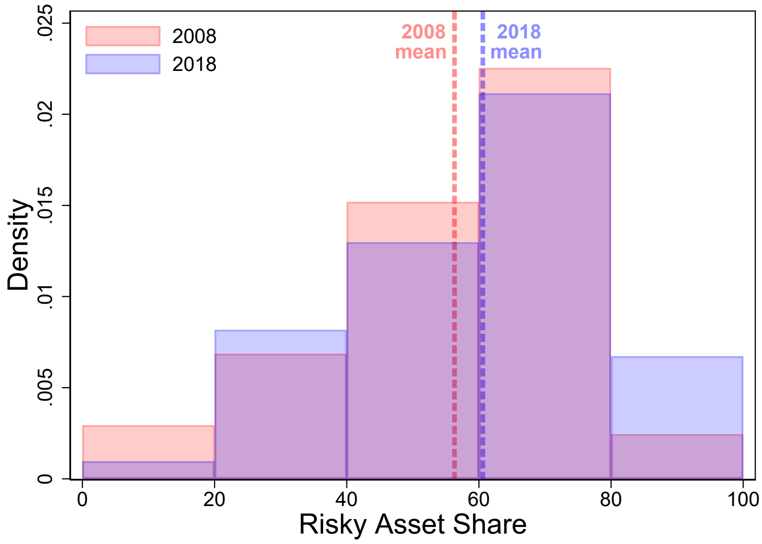
Notes: This figure shows the average portfolio composition by asset class, denoted as a percentage of total assets, for the pooled sample as well as European and non-European pension funds, respectively. Fixed income includes all types of bonds, alternative comprises of infrastructure, real estate and commodities. Others includes pooled investment vehicles such as UCITs.

When comparing the two geographical regions, European pension funds have a higher proportion of fixed income in their portfolios compared to non-European funds. In turn, non-European funds invest more in loans and alternative assets. Cash holdings make up an equal fraction for the two groups, but European funds have a higher share of "other" investments. Consequently, non-European pension funds tend to have riskier balance sheets (see also Table 2).

Figure 2 provides further information on the evolution of portfolio risk over time. It depicts the cross-sectional distributions of pension funds' risky asset shares in 2008 (colored in red) and 2018 (colored in blue). Over time, the distribution has markedly shifted to the right, indicating an increase in portfolio risk over the 10-year period. The average fund in the sample saw a 4.3 percentage point increase in its risky asset share, from 56.3% in 2008 to 60.6% in 2018, as represented by the dashed lines. A simple t-test confirms that the means of the two distributions are different. Further, both European and non-European pension funds increased their exposure to risky assets, with increases of 4 and 6 percentage points, respectively.

One concern is that the definition of risky and safe asset classes is too broad, with relatively safer assets classified as risky. Unfortunately the data do not permit a direct way of quantifying the riskiness *within* an asset class. Based on annual return data, it is however possible to compute a rolling market beta of the risky portfolio

Figure 2: Risky asset share, 2008 and 2018



Notes: This figure shows the cross-sectional distribution of the risky asset share across funds in 2008 (red) and 2018 (blue). Dashed lines denote the respective sample means.

relative to returns of the MSCI World benchmark index. The beta estimates are generally below one depict a similar upward trend over the past decade, on average (see Appendix A.6).

Figure 2 hides important heterogeneity within the class of risky assets and across countries. As Table 2 and Figure 1 illustrate, balance sheet compositions differ between European and non-European funds. In the same vein, they might have a preference for some risky asset classes when interest rates fall.

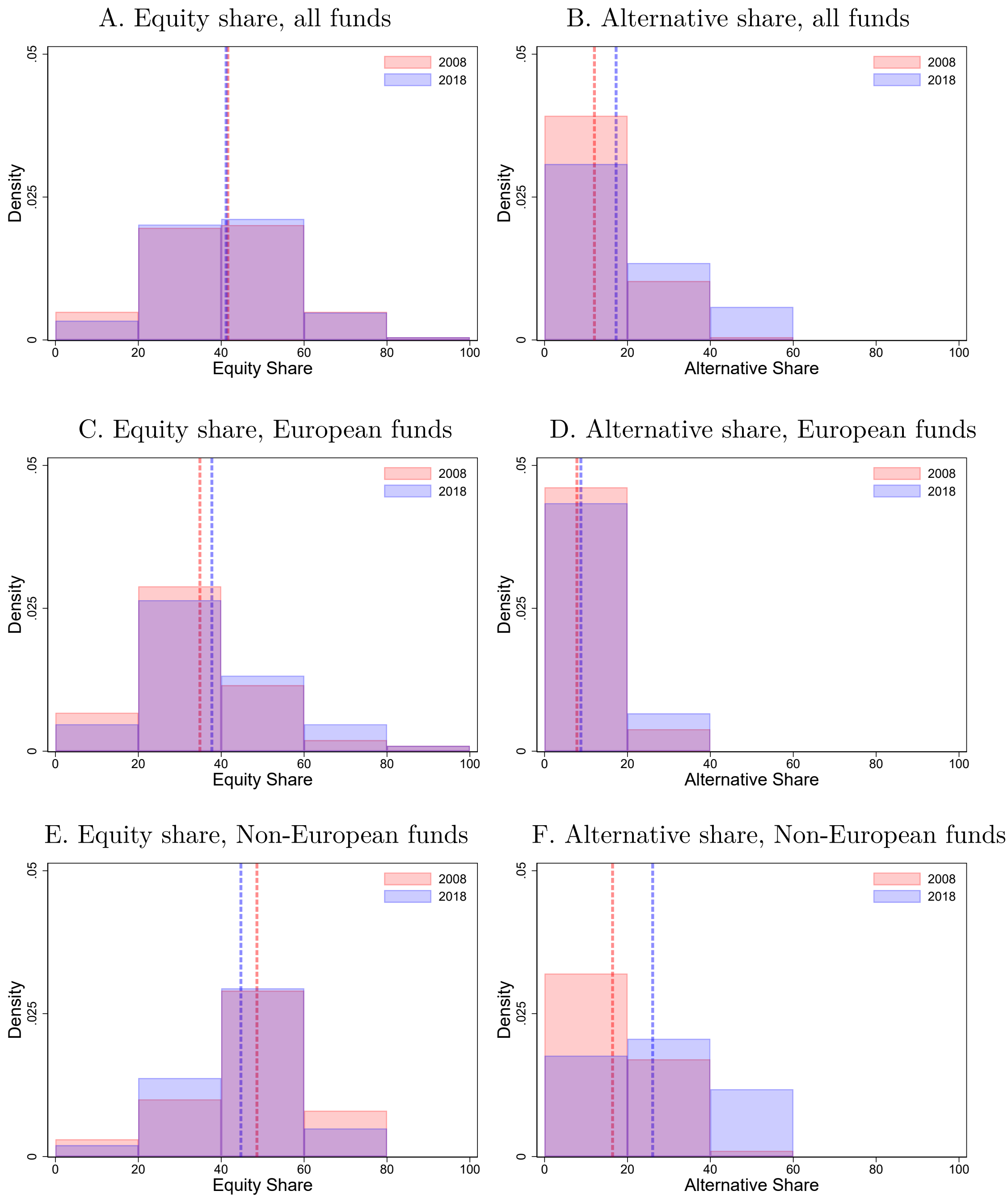
In Figure 3, I shed light on equity and alternative investments across different regions. I start by reproducing Figure 2 using the share of public equities (panel A) and alternative assets (panel B) relative to total assets, for the average pension fund. A comparison of the two figures indicates that average funds' increase in risky assets between 2008 and 2018 was driven taking on more alternative assets, at about 6 percentage points. This underpins the results of Ivashina and Lerner (2018), who document a similar trend after 2008. Conversely, the distribution of the equity share across funds appears quite stable over the 10-year span.

Panels C through F display similar histograms for funds located both inside and outside of Europe. Two key patterns emerge from this analysis: First, the shift towards alternative asset holdings is primarily driven by pension funds outside of Europe, as shown in Panel F. Indeed, non-European pension funds increased their exposure to alternative assets by almost 10 percentage points, on average. European funds on the other hand (panel D) only shift marginally towards alternative asset classes.

Second, in Panel C we see a stronger increase in the exposure to public equities by European funds. On average, a fund increased its weight of public equities by four percentage points over the course of ten years, as compared to 2018. North American and Asian funds, on the other hand, decreased their share of equity holdings significantly.

In sum, pension fund have increased their exposure to risky assets over the last decade, albeit through different asset classes. Whereas European pension funds mainly increased their equity exposure, funds based outside of Europe favored alternative assets. Comparing panels C and E, one interpretation is that pension funds outside of Europe were forced to look for alternative investments because they already had a high equity exposure in 2008. Conversely, European funds initially held fewer risky assets, and tilted their portfolios more towards equity instead of alternative investments.

Figure 3: Equity and alternative share, 2008-2018



Notes: This figure shows the cross-sectional distribution of the equity and alternative assets share across funds in 2008 (red) and 2018 (blue). Dashed lines denote the respective sample means. Panels A, C and E focus on the share of equity, the remaining panels on the alternative share, relative to total assets. Panels A and B include all funds, panels C and D (E and F) are based only on European (Non-European) pension funds.

3 Measuring financial decisions: Conceptual framework

After documenting descriptively that pension funds' risk-taking has increased substantially over the past years, this section introduces a conceptual framework for assessing the drivers of investments in risky assets over time. Specifically, I isolate two channels, related to the risk premium and risk-free rate to quantify their importance. Before the analysis, I begin by constructing the main dependent variable, which captures the active decisions of funds to invest in riskier asset classes that is unaffected by valuation effects.

3.1 Measuring risk-taking

Pension funds invest capital on behalf of their pensioners in both safe and risky assets. Pension funds receive cash inflows from active members and their employers in addition to returns and dividends from existing investments, while also paying benefits to retirees. Pension funds generally avoid using leverage and instead adjust their portfolio weights to alter expected financial returns (see e.g., Lu et al. 2019).[9] Consequently, the ratio of risky assets relative to the total portfolio is a key variable to understand funds' risk-taking over time.

Formally, I define the risky share of assets, $Share_{it}$, of fund i in year t as the weight of risky assets relative to the total portfolio,

$$Share_{it} = \frac{Equity_{it} + Alternative_{it} + Corporate\,Bonds_{it} + Loans_{it}}{Total_{it}}, \tag{1}$$

where $Equity_{it}$, $Alternative_{it}$, $Corporate\,Bonds_{it}$, $Loans_{it}$ and $Total_{it}$ denote the balances of equities, alternative assets, corporate bonds, loans and total assets in fund i's portfolio at the end of year t, respectively.[10]

The dynamics of a pension funds' risky asset share over time can be deconstructed into two parts. The first component is due to the differential rates of return on the risky and safe portfolios, which mechanically affect $Share_{it}$. For instance, during bullish stock market periods with high equity returns, $Share_{it}$ increases automatically, with the opposite occurs during bearish periods with negative equity returns.

[9] In recent years some funds in the US have started to use leverage, but this is the exception rather than the rule. See https://www.forbes.com/sites/simonmoore/2021/11/16/major-pension-fund-adds-leverage-as-assets-push-half-a-trillion/?sh=5ecc0bcc27e1.

[10] I test alternative definitions of the risky asset share in Appendix A.1. The main results remain robust to allocating corporate bonds and loans to the safe asset category or excluding alternative investments.

The second component is associated with active management decisions, as funds make choices to purchase or sell risky and safe assets. In practice, many pension funds establish a range of target portfolio weights at the start of the year, which they adjust periodically. However, changes in the macro-financial environment during the year may lead pension funds to deviate from their initial weights to maximize returns. The focus of this study is to explain both types of changes in portfolio weights, which reflect active management decisions made in response to changing investment conditions.

To empirically separate the two components, I adopt an approach in the spirit of Hau and Rey (2008) and Calvet, Campbell, and Sodini (2009). First, I define a fund's rate of return during year t on both the total portfolio, r_{it}^T, and the risky portfolio, r_{it}^R. In cases where return data are not directly available, I calculate them based on opening and closing annual positions, and net purchases. All returns are net of dividends or interest payments. Then, I determine the intermediate implied risky asset share that results from differential rates of return,

$$Passive\,Share_{it} = \left[\frac{1+r_{it}^R}{1+r_{it}^T}\right] Share_{it-1} \ , \tag{2}$$

where $Share_{it-1}$ denotes the risky asset share of fund i at the beginning of the year t (or at the end of the previous year $t-1$).

Under a passive holding strategy, $Passive\,Share_{it}$ and $Share_{it}$ would be identical. However, any difference between the two reflects active management decisions, either from the allocation of new capital, or the re-allocation of existing capital across asset classes.

To separate the active component, I calculate the change in the risky asset share that is not explained by passive changes,

$$\Delta Active_{it} = Share_{it} - Passive\,Share_{it} \ , \tag{3}$$

as the difference between the actual observed risky asset share and the implied risky asset share under a passive holding strategy. By construction, the passive and active components make up the total change in $Share_{it}$ between two periods.

Importantly, $\Delta Active_{it}$ reflects all active decisions made by fund managers to alter portfolio weights in response to changing expected returns or macro-financial conditions in a given year. As such, it serves as an effective proxy for evaluating pension funds' risk-taking over time.

3.2 Determinants of risk-taking

Changes in the strategic asset allocation of pension funds towards risky assets in principle depend on many factors. To identify the impact of interest rate changes on pension funds' financial risk-taking, controlling for risk premiums and financial conditions is especially important. To that end, I adopt an approach similar to Rousová and Giuzio (2019) to calculate a fund-specific and time-varying risk premium,

$$RP_{it} = r_{it}^{R} - RF_{it} \ , \tag{4}$$

where RF_{it} is the short-term risk-free rate in the home country of pension fund i in year t. Although this may not perfectly reflect the expectations of future returns, Andonov and Rauh (2022) argue that such expectations are formed on the basis of past experience and persist over time. As a robustness exercise, I consider a smoothed version of the risk premium, and a forward-looking alternative proxy based on Gilchrist and Zakrajšek (2012), detailed in Appendix A.2.

Empirically, I use data on 3-month interbank rates as a proxy the domestic risk-free rate (e.g., Harvey 1991). I test various alternative risk-free rates, including domestic central bank monetary policy rates and Wu and Xia (2016) shadow rates unconstrained by the zero lower bound, as well as long-term interest rates up to 10-year maturity. All interest rate variables are annual averages computed per accounting year of a given fund.[11]

4 Econometric analysis

4.1 Baseline specification

This section outlines the empirical strategy to assess reach for yield by pension funds, based on the theoretical framework. I begin with the baseline regression (panel–OLS),

$$\Delta Active_{it} = \alpha + \beta_1 \, RF_{it} + \beta_2 \, RP_{it} + \theta_i + \delta_t + \epsilon_{it} \ , \tag{5}$$

where $\Delta Active_{it}$, RF_{it} and RP_{it} are defined above. θ_i and δ_t are fund and year fixed effects, capturing any time-varying or investor-specific unobserved variation. α is a constant and ϵ_{it} is an error term.

This laboratory allows to test different hypotheses related to pension funds'

[11] For instance, most funds based in Europe report on December 31, whereas the majority US funds' fiscal years end on June 30.

investment behavior. First, the coefficient β_1 captures a funds' tendency to reach for yield. A negative loading indicates that pension funds actively increase (decrease) their exposure to risky assets when risk-free rates decrease (increase). In line with the previous literature on US pension funds (Chodorow-Reich 2014, Lu et al. 2019), I expect $\beta_1 < 0$.

Second, changes in risk-taking in response to the risk premium are gauged by β_2. A negative coefficient indicates counter-cyclical investment behavior, i.e. funds buying (selling) risky assets after their returns have been high (low). In line with the previous literature (e.g., Timmer 2018), I expect $\beta_2 < 0$.

Importantly, this empirical specification assumes that there is no reverse causality from pension funds' investment behavior to central bank policy which governs risk-free rates. Since pension funds predominantly hold long-term bonds (see e.g., Greenwood and Vissing-Jorgensen 2018), I argue reverse causality is less of a concern at shorter maturities. Moreover, the focus on individual pension funds, albeit large in size, implies that they are price takers in the market for short-term government bonds.[12]

To address potential endogeneity issues I adopt an instrumental variables approach and use monetary policy surprises, to capture exogenous variation in the risk-free rate. First, I use changes in the domestic central banks' balance sheet size as a driver of risk-free rates that is unaffected by pension fund behavior.[13] Second, I draw on established monetary policy surprises from Nakamura and Steinsson (2018) for Non-European funds and Altavilla et al. (2019) for European funds, respectively. Further, I employ the interest rate surprise series for the 3-month federal funds rate and EIONA 3-month rate by Jarociński and Karadi (2020), with similar results. All policy shocks are aggregated per fiscal year for each fund.

I perform various robustness checks on the baseline model: First, I swap the risk-free rate with the monetary policy rate and Wu and Xia (2016) shadow rates. Second, I use alternative proxies for the risk premium, including a smoothed version and the excess bond premium (Gilchrist and Zakrajšek 2012). Third, I account for potential confounding factors, including demographic trends and changes in central bank balance sheet sizes. Fourth, I verify that any financial regulation of pension funds does not influence their increased risk-taking. The results are robust to these alternative specifications.

[12] Greenwood and Vissing-Jorgensen (2018) suggest banks hold more than 70% of bonds with maturity below one year, based on data from Denmark.

[13] Data on national central bank balance sheet size, scaled by GDP, are retrieved from FRED.

4.2 Effect of funds' characteristics

The likelihood of reaching for yield potentially varies across different types of pension funds. First, a lower funding status and discount rate promotes risk-taking behavior by US pension funds, to avoid funding shortfalls (e.g., Lu et al. 2019). Second, demographic factors such as a pension funds' maturity or composition of retirees influence risk-taking (e.g., Rauh 2009, Andonov, Bauer, and Cremers 2017). Third, pension funds may reach for yield differently based on the initial level of risk in their balance sheets. I use proxies for these factors and include them separately in the regression, including interaction terms with the risk-free rate.

The following placeholder regression illustrates the augmented baseline model including the interaction terms,

$$\begin{aligned} \Delta Active_{it} =& \alpha + \beta_1\, RF_{it} + \beta_2\, RP_{it} + \beta_3\, Safe\,Share_{it-1} \\ & + \beta_4\, RF_{it} \times Safe\,Share_{it-1} + \theta_i + \delta_t + \epsilon_{it}\ , \end{aligned} \tag{6}$$

where $Safe\,Share_{it-1}$ is pension fund i's share of safe assets (the counterpart of the risky asset share) at the start of year t. I estimate a similar model for the remaining variables described above.

Differences in reach for yield may also occur across geographical regions. To test this, I add dummy variables indicating a fund's domicile to the baseline model, differentiating between European and non-European funds,

$$\begin{aligned} \Delta Active_{it} =& \alpha + \beta_1\, RF_{it} \times \mathbf{1}_{EU} + \beta_2\, RF_{it} \times \mathbf{1}_{Non-EU} \\ & + \beta_3\, RP_{it} \times \mathbf{1}_{EU} + \beta_4\, RP_{it} \times \mathbf{1}_{Non-EU} + \theta_i + \delta_t + \epsilon_{it}\ , \end{aligned} \tag{7}$$

where $\mathbf{1}_{EU}$ defines European funds and $\mathbf{1}_{Non-EU}$ non-European funds.

I use similar dummy variables to test for non-linear effects of reach for yield over time, by dividing the sample in two parts, before and after 2010. Lastly, I estimate a model with double interaction terms, $RF_{it} \times \mathbf{1}_{Year \leq 2009} \times \mathbf{1}_{EU}$, to determine whether reach for yield by European and non-European pension funds is more pronounced in different sample periods.

5 Results

In this section, I presents the different set of results. I start with the baseline analysis, followed by estimates conditional on fund-level characteristics. Next, I examine time-varying results and analyze the differences in funds based inside and outside of Europe. Finally, I address potential confounding factors and demonstrate the robustness of the results to alternative specifications

5.1 Main result

The results on the relationship between interest rates and risk-taking, based on Equation 5, is presented in Table 3. Column 1 displays the estimates for a basic specification that only controls for fund fixed effects. The risk-free rate and the risk premium enter negatively and with statistically significant coefficients. The former is consistent with reach for yield, pension funds actively shift their portfolios towards riskier assets as risk-free rates decrease. The latter suggests that pension funds behave as counter-cyclical investors, reducing their exposure to risky assets after high returns.

Column 2 of Table 3 shows the baseline specification with year fixed effects. The coefficients remain negative and statistically significant at the 1 percent confidence level. Quantitatively, a 1 percent point decrease in the risk-free rate implies an increase in active risk-taking by 0.66 percentage points, per year. Across the countries included in this study, the average risk-free rate decreased by more than 3 percentage points in the aftermath of the global financial crisis alone, which would imply a cumulative 2 percentage point increase in risky assets by pension funds. This finding aligns with prior studies on US pension funds by Chodorow-Reich (2014) and Lu et al. (2019), and other long-term investors (e.g., Ozdagli and Wang 2019, Di Maggio and Kacperczyk 2017).

Column 2 reinforces the finding of counter-cyclical investment behavior by pension funds. In quantitative terms, a 1 percentage point increase in the risk premium, due to an increase in returns if risky assets over the risk-free rate, is associated with a 0.10 percentage point decrease in the ratio of risky assets of pension funds. This is consistent with the findings of Timmer (2018).

In the baseline analysis, I use domestic interest rates with a maturity of 3 months (e.g. T-bills in the US). I test alternative risk-free rates in columns 3–5 of Table 3. First, I employ the domestic monetary policy rate, with very similar results in quantitative terms. Importantly, pension funds in the Euro area share the same risk-free rate in this specification. Column 4 is based on central bank policy shadow rates (Wu and Xia 2016), which are not constrained by the zero lower bound. Data are available only for the United States, United Kingdom and Euro area. The coefficient of RF_{it} is smaller in magnitude but remains precisely estimated. I estimate the baseline model using long-term interest rates at 10-year maturity in column 5, with results that remain both sizeable and statistically significant.[14]

Table 3: Baseline regression reach for yield (active increase of risky asset exposure)

	3-month rate		Policy rate	Shadow rate	10-year rate
	(1)	(2)	(3)	(4)	(5)
RF_{it}	-0.20***	-0.66***	-0.65***	-0.30***	-0.64***
	(0.07)	(0.16)	(0.16)	(0.08)	(0.24)
RP_{it}	-0.10***	-0.10***	-0.09***	-0.09***	-0.09***
	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)
Constant	0.58***	1.43	1.28	2.68**	1.62
	(0.13)	(1.30)	(1.32)	(1.02)	(1.59)
Observations	1,831	1,831	1,829	1,212	1,831
Funds	105	105	105	71	105
R^2	0.10	0.14	0.14	0.16	0.14
Fund FE	Yes	Yes	Yes	Yes	Yes
Time FE	No	Yes	Yes	Yes	Yes

Notes: The dependent variable is the active change in the share of risky assets of fund i during year t. RF_{it} and RP_{it} are the risk-free rate and risk premium, as constructed above, respectively. Columns 1–2 are based on 3-month risk-free rates, columns 3 and 4 use monetary policy rate and shadow rates, respectively. Column 5 is based on 10-year interest rates to proxy risk-free rates. All regressions include robust standard errors clustered on fund. Significance levels denoted by *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Long-term interest rates are potentially prone to be affected by pension fund behavior, since they are sizeable holders of domestic government debt. As outlined above, I argue that using short-term rates partially alleviates this concerns, because pension funds mainly hold longer dated bonds.[15] This is also emphasized by Greenwood and Vissing-Jorgensen (2018), who document a strong effect of pension funds (and insurers) on asset prices only on the long end of the yield curve. Indeed, under the assumption that pension funds' asset demand also affects yields at shorter maturities, one might expect pension funds to increase their exposure to short-term government bonds during the period after 2008. Conversely, the negative correlation between pensions' demand for safe assets and risk-free rates would suggest that the estimates in this paper are lower bounds.

To credibly address potential endogeneity issues, I estimate Equation 5 using an instrumental variables (IV) approach instead of OLS. Specifically, I exploit the expansion of domestic central banks' balance sheets as an exogenous driver of local interest rates, that is plausibly unaffected by pension funds investment behavior.

[14]Appendix A.5 shows that the results remain consistent when estimating size-weighted regressions.

[15]See e.g., https://www.ecb.europa.eu/pub/financial-stability/fsr/8b0aebc817.en.html.

The estimates from the IV regressions are displayed in Table 4. Across specifications, the change in central bank balance sheet size to GDP has the expected negative sign and is precisely estimated. In other words, balance sheet expansions are associated with a fall in risk-free rates. The high Montiel-Plueger F-statistics suggest strong instruments in all four cases.

Table 4: Instrumental variables regression

	$\Delta Active_{it}$		$\Delta Active_{it}^{EQALT}$	
	3-month rate	Policy rate	3-month rate	Policy rate
	(1)	(2)	(3)	(4)
RF_{it}	-1.59**	-1.66**	-1.61**	-1.69**
	(0.79)	(0.81)	(0.82)	(0.85)
RP_{it}	-0.11***	-0.10***	-0.11***	-0.10***
	(0.02)	(0.02)	(0.02)	(0.01)
Constant	6.39	6.47	6.60	6.71
	(4.47)	(4.46)	(4.42)	(4.42)
Observations	1,745	1,743	1,744	1,742
Funds	105	105	105	105
R^2	0.13	0.13	0.14	0.14
Fund & Time FE	Yes	Yes	Yes	Yes
Montiel-Plueger F-stat.	28.436	32.317	28.537	32.283

Notes: The dependent variable is the active change in the share of risky assets of fund i during year t. In columns 3 and 4, only equities and alternative investments are classified as risky. RF_{it} and RP_{it} are the risk-free rate and risk premium, as constructed above, respectively. Columns 1 and 3 are based on 3-month risk-free rates, columns 2 and 4 use the monetary policy rate, respectively. Interest rates are instrumented using the change in domestic central banks' assets to GDP. All regressions include robust standard errors clustered on fund. Significance levels denoted by *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

The IV-based results reinforce the results of the OLS regressions. The coefficient of the instrumented RF_{it} is negative in all specifications and statistically significant at the 5 percent confidence level. This holds irrespective of using 3-month interbank or monetary policy rates to proxy RF_{it}. Quantitatively, the estimates are larger than the OLS-based coefficients which points to a potential negative bias, related to fewer risky asset purchases contributing to a fall in risk-free rates. Moreover, the coefficients confirm the counter-cyclical behavior of pension funds. The last two columns of Table 4 are based on a dependent variable classifying only equities and alternative investments as risky (see also Appendix A.1). Reassuringly, the results remain virtually unchanged.

In addition, I employ monetary policy surprises to isolate the exogenous compo-

Table 5: Reach for yield with monetary policy surprises

	All countries	Excl. Asia	USA, Euro area
	(1)	(2)	(3)
$Shock_{it}$	-5.09**	-4.82**	-8.74***
	(2.30)	(2.32)	(3.20)
RP_{it}	-0.09***	-0.09***	-0.10***
	(0.01)	(0.02)	(0.02)
Constant	-2.26**	-2.28**	-2.70***
	(0.97)	(0.97)	(0.47)
Observations	1,789	1,755	1,110
Funds	105	102	66
R^2	0.13	0.13	0.19
Fund & Time FE	Yes	Yes	Yes

Notes: The dependent variable is the active change in the share of risky assets of fund i during year t. $Shock_{it}$ is the aggregated monetary policy surprise shock from Nakamura and Steinsson (2018) and Altavilla et al. (2019), respectively. Column 1 uses funds from all countries. Columns 2–3 exclude Japanese and Korean, as well as UK, Swiss, Canadian, Norwegian and Swedish pension funds, respectively. RP_{it} is the risk premium, as constructed above. All regressions include robust standard errors clustered on fund. Significance levels denoted by *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

nent of changes in the risk-free rate. To ensure a sufficiently large sample, I use the Fed shocks for all non-European and the ECB shocks for the European economies in the first specification. To ensure that the response in risk-taking to policy surprises is driven by monetary policy and not other news contained in the central bank announcements, I repeat the analysis using policy surprises by Jarociński and Karadi (2020). The estimates are comparable, and presented in Appendix A.3.

Table 5 presents the results. Consistent with the baseline estimation, the policy rate surprises enter with a negative sign and are statistically significant at the 5% confidence level, across specifications. In quantitative terms, a negative one standard deviation monetary policy surprise is associated with an active 0.46 percentage point increase in the risky asset share by pension funds (namely, 0.091×-5.09). This is robust to excluding pension funds from Asian countries that might not be affected by Fed policy (column 2).

Column 3 includes only US, Canadian, Euro area and Danish pension funds, to ensure the monetary policy surprises indeed directly affect the domestic financial conditions.[16] The estimated effects of monetary policy surprises on risk-taking by

[16] Although Denmark is not part of the Euro currency area, Danmarks Nationalbank follows a fixed exchange rate policy against the Euro, see https://nationalbanken.dk/fixed-exchange-rate-policy.

pension funds are significantly and more precise larger for this sub-sample, potentially due to the fact that it focuses on funds directly affected by the monetary policy changes. Throughout, the results are also consistent with counter-cyclical investment behavior by pension funds.

In sum, there is robust evidence of reach for yield by pension funds in response to falling domestic risk-free rates. This finding is consistent for different risk-free rate proxies, and when using an IV regression or established monetary policy surprises. Further, test whether the results are sensitive to classification of risky assets, I use an alternative approach in Appendix A.1.

5.2 Fund heterogeneity

After establishing that the average fund in the sample reaches for yield, this section asks whether this tendency differs across pension funds. I focus on two dimensions in particular: a funds' initial share of safe assets and its funding status. Both reflect pension funds' capacity to accommodate more risky assets on their balance sheet. Moreover, from a financial stability perspective, it is important to understand whether initially riskier or underfunded pension funds are more likely to reach for yield.

Column 1 of Table 6 includes a fund's initial share of safe assets in the regression. The estimated coefficient is positive and statistically significant at the 1% confidence level, suggesting that initially safer pension funds purchase more risky assets, on average. This points to a potentially complementary long-term portfolio adjustment towards more risky assets. The coefficients of the risk-free rate and risk premium remain unchanged. Next, I add an interaction term to assess whether reach for yield is more pronounced for funds with riskier balance sheets. The negative and statistically significant coefficient (at the 5% level) implies that reach for yield is indeed stronger in pension funds with fewer risky assets initially.

Figure 4 illustrates the effect graphically, by showing the reach for yield coefficient for different levels of the initial share of safe assets, including 95% confidence bands (dotted lines). For instance, a pension fund holding 80% safe assets actively increases its risky asset exposure by two times more compared to a fund with 20% safe assets. For pension funds with very risky balance sheets (safe share below 10%), the reach for yield coefficient loses statistical significance.

Next, I ask whether a pension funds' funding status promotes risk-taking. For instance, do underfunded pension plans reach for yield more to "gamble for resurrection"? Column 3 of Table 6 includes the initial funding status as a control variable. The estimated coefficient is close to zero and imprecisely, suggesting that purchases

Table 6: Reach for yield conditional on fund characteristics

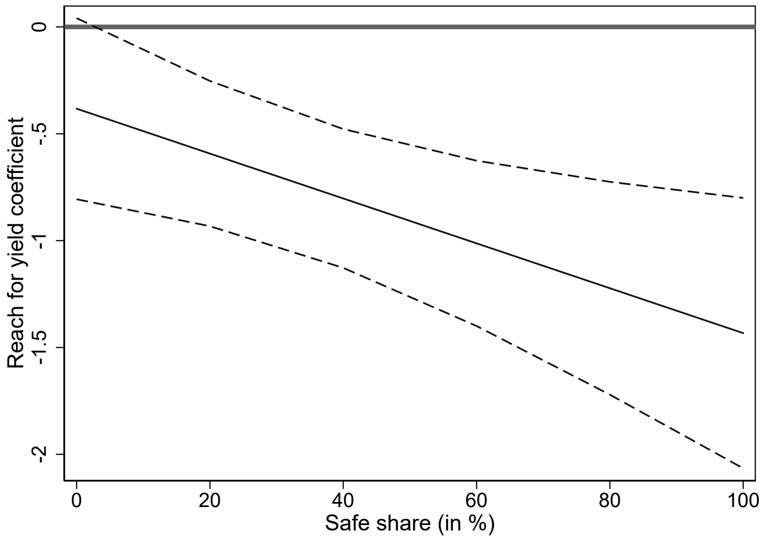
	(1)	(2)	(3)	(4)
RF_{it}	-0.68***	-0.75***	-0.39*	-0.55**
	(0.17)	(0.19)	(0.22)	(0.22)
RP_{it}	-0.11***	-0.11***	-0.11***	-0.11***
	(0.01)	(0.02)	(0.01)	(0.02)
$Safe\,Share_{it-1}$	0.16***		0.17***	
	(0.02)		(0.02)	
$Safe\,Share_{it-1} \times RF_{it}$			-0.01**	
			(0.00)	
$Funding\,Status_{it-1}$		-0.01		-0.01
		(0.00)		(0.00)
$Funding\,Status_{it-1} \times RF_{it}$				-0.00***
				(0.00)
Constant	-4.85***	5.27***	-4.54***	5.68***
	(1.61)	(1.64)	(1.70)	(1.67)
Observations	1,830	1,348	1,830	1,348
Funds	105	85	105	85
R^2	0.10	0.16	0.10	0.15
Fund & Time FE	Yes	Yes	Yes	Yes

Notes: The dependent variable is the active change in the share of risky assets of fund i during year t. $Safe\,Share_{it-1}$ and $Funding\,Status_{it-1}$ are the share of safe assets (in %) and the funding status (in %) by a fund i at the beginning of year t, respectively. All regressions include robust standard errors clustered on fund. Significance levels denoted by *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

of risky assets do not depend on funding status. Column 4 adds an interaction term with the risk-free rate, which is negative and statistically significant at the 1% confidence level. Intuitively, this points to funds that are less underfunded initially reaching for yield more when interest rates fall. Since this this analysis relies on actual funding status data of US funds, the estimated interaction effects should be seen as lower bounds.

Overall, the results point to reach for yield being most pronounced for funds with more capacity to take risks, either less underfunded or holding fewer risky assets initially.

Figure 4: Interaction between reach for yield and initial balance sheet



Notes: This figure shows the reach for yield effect different initial rates of the initial safe share. The respective estimates are contained in Column 2 of Table 6. The dotted lines denote 95% confidence bands.

5.3 Reach for yield over time

In this section, I turn to asking whether the tendency to reach for yield in response to falling interest rates is potentially non-linear and varying over time. For example, do pension funds reach for yield more when interest rates are very low, compared to rates in modest positive territory?

Empirically, I augment the baseline model by adding dummy variables denoting that denote time and interest rate regimes, and interact them with the risk-free rate variable. I begin by using dummy variables that divide the sample into two phases: an early phase before 2010 and a late phase during which interest rates were lower. Column 1 of Table 7 displays the results. The reach for yield coefficients are identical in the first and second half of the sample, with similar levels and statistical significance compared to the overall coefficient.

Next, Column 2 adds a dummy variable denoting episodes with positive and non-positive risk-free rates, to test whether it affects reach for yield. The estimated coefficient is four times larger in the non-positive interest rate environment, compared to the positive territory, and remains statistically significant, though only at the 10% confidence level. In Column 3, I use similar dummy variables for whether the risk-free rate is above or below its country-specific sample average. The findings suggest that reach for yield is stronger when risk-free rates are below the sample mean, although the difference between the two coefficients is not statistically significant.

Across specifications, the risk premium coefficient remains of similar size and

Table 7: Reach for yield over time

	(1)	(2)	(3)
$RF_{it} \times \mathbf{1}_{Year \leq 2009}$	-0.66***		
	(0.21)		
$RF_{it} \times \mathbf{1}_{Year > 2009}$	-0.66***		
	(0.20)		
$RF_{it} \times \mathbf{1}_{RF_{it} > 0}$		-0.67***	
		(0.16)	
$RF_{it} \times \mathbf{1}_{RF_{it} \leq 0}$		-2.59*	
		(1.42)	
$RF_{it} \times \mathbf{1}_{RF_{it} > \overline{RF_i}}$			-0.71***
			(0.23)
$RF_{it} \times \mathbf{1}_{RF_{it} < \overline{RF_i}}$			-0.81***
			(0.21)
RP_{it}	-0.10***	-0.10***	-0.10***
	(0.01)	(0.01)	(0.01)
Constant	1.45	1.50	1.54
	(1.53)	(1.34)	(1.35)
Observations	1,831	1,831	1,831
Funds	105	105	105
R^2	0.14	0.14	0.14
Fund & Time FE	Yes	Yes	Yes

Notes: The dependent variable is the active change in the share of risky assets of fund i during year t. $\mathbf{1}_{Year \leq 2009}$ and $\mathbf{1}_{Year > 2009}$ are dummy variables denoting the period leading up to and after 2009, respectively. $\mathbf{1}_{RF_{it} > 0}$ and $\mathbf{1}_{RF_{it} \leq 0}$ are dummy variables indicating whether the risk-free rate is in positive or non-positive territory. $\mathbf{1}_{RF_{it} > \overline{RF_i}}$ and $\mathbf{1}_{RF_{it} < \overline{RF_i}}$ denote whether the risk-free rate is above or below its sample average, where $\overline{RF_i}$ is the country-specific sample average. RF_{it} and RP_{it} are the risk-free rate and risk premium, as constructed above, respectively. All respective dummy variables are included in the regression, but their coefficients not reported. All regressions include robust standard errors clustered on fund. Significance levels denoted by *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

precision as in the baseline model. Overall, these findings provide suggestive evidence that reach for yield may be exacerbated when risk-free rates are already low and potentially in negative territory.

5.4 Regional heterogeneity

In this section, I explore whether European and non-European funds are equally likely to reach for yield, given that they face different initial balance sheet compositions, funding ratios and risk-free rates (compare Table 2). This exercise is also in the spirit of Andonov, Bauer, and Cremers (2017), who argue that public pension funds in the US take on more risk than their European counterparts to maintain higher discount rates. I use dummy variables denoting the two respective geographical regions.

Column 1 of Table 8 includes the geographic dummy variables and their interaction terms with the risk-free rate and risk premium, respectively. First, the reach for yield channel appears to be stronger for European-based pension funds compared to their non-European counterparts, although the difference is not statistically significant. Second, the results suggest that non-European investors display more counter-cyclical behavior, with a coefficient that is about twice as large and statistically significant at the 1% confidence level.

Column 2 tests for differences between the two groups before and after 2010. I find evidence of both regions' funds reaching for yield in the first half of the sample, with negative and statistically significant coefficients (at the 10% and 5% levels, respectively). The coefficient for European-based funds is larger, but the difference is not statistically significant. In the latter half of the sample, there is a clear difference in reach for yield: the coefficient for European pension funds nearly triples in size and is significant at the 1% confidence level. Conversely, the coefficient for non-European funds changes sign after 2010, with large standard errors. This suggests that while all pension funds reach for yield before 2010, European funds do so much more aggressively in the latter half of the sample, while non-European funds stop.

I illustrate this finding graphically, by plotting the reach for yield coefficients for European and non-European pension funds before and after 2010 in Figure 5. In the first half of the sample, the reach for yield coefficients are both around -0.5 with overlapping error bands around the point estimates. In the second period, the estimated coefficients diverge, clearly visible by comparing the respective error bands. Quantitatively, this suggests that, in response to a 1 percentage point fall in the domestic risk-free rate, European pension funds increase their risky asset exposure more than proportionally. For non-European pension funds there is no evidence of reach for yield behavior in the latter half of the sample.

Intuitively, this finding can be rationalized based on the previous results showing reach for yield is exacerbated under lower interest rates, and for less underfunded funds with fewer risky assets initially. On average, European pension funds hold fewer risky assets and are less underfunded compared to their non-European counterparts.

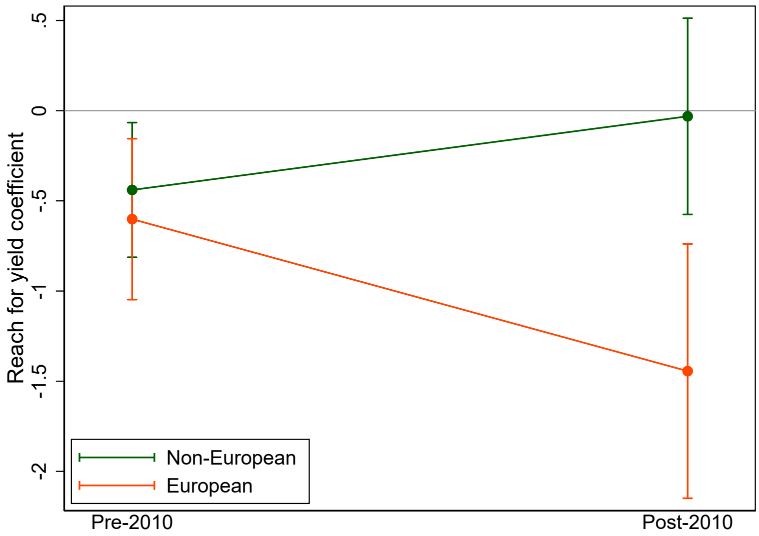
Table 8: Reach for yield by European pension funds over time

	(1)	(2)
$\mathbf{1}_{Non-EU} \times RF_{it}$	-0.46**	
	(0.18)	
$\mathbf{1}_{EU} \times RF_{it}$	-0.48***	
	(0.18)	
$\mathbf{1}_{Non-EU} \times RP_{it}$	-0.13***	-0.14***
	(0.01)	(0.01)
$\mathbf{1}_{EU} \times RP_{it}$	-0.06**	-0.06***
	(0.02)	(0.02)
$\mathbf{1}_{Non-EU} \times \mathbf{1}_{Year \leq 2009} \times RF_{it}$		-0.44*
		(0.23)
$\mathbf{1}_{Non-EU} \times \mathbf{1}_{Year > 2009} \times RF_{it}$		-0.03
		(0.33)
$\mathbf{1}_{EU} \times \mathbf{1}_{Year \leq 2009} \times RF_{it}$		-0.60**
		(0.27)
$\mathbf{1}_{EU} \times \mathbf{1}_{Year > 2009} \times RF_{it}$		-1.44***
		(0.43)
Constant	0.56	0.70
	(1.31)	(1.63)
Observations	1,831	1,831
Funds	105	105
R^2	0.15	0.16
Fund & Time FE	Yes	Yes

Notes: The dependent variable is the active change in the share of risky assets of fund i during year t. $\mathbf{1}_{EU}$ is a dummy variable equal to one for funds domiciled in the Euro area, Scandinavia, Switzerland and the UK. $\mathbf{1}_{Non-EU}$ is a similar dummy variable for funds from the US, Canada and Asia. $\mathbf{1}_{Year \leq 2009}$ and $\mathbf{1}_{Year > 2009}$ are dummy variables denoting the period leading up to and after 2009, respectively. All respective dummy variables are included in the regression, but their coefficients not reported. All regressions include robust standard errors clustered on fund. Significance levels denoted by *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Moreover, European countries had lower interest rates compared to the US and Canada.

Figure 5: Reach for yield by region over time



Notes: This figure shows the reach for yield effect for European and non-European funds in the first and second half of the sample, respectively. The respective estimates are contained in Column 2 of Table 8. Confidence bands are based on 90% significance levels.

5.5 Robustness

In this section I perform additional robustness checks to verify the consistency of the baseline results. First, I control for demographic trends that affect both the importance of the pension fund industry and risk-free rates. Second, I account for the effects of unconventional monetary policy during my sample period. Third, I add a proxy for domestic pension fund regulation to rule out that they are driving the results.

Column 1 of Table 9 includes a fund's initial balance sheet size in the regression. The estimated coefficient is negative but with very large standard errors, while the main effects remain unchanged. As a second demographic variable, I include the share of retirees to the total number of members in the regression. The variable is only available for a limited number of funds, and its effect is estimated to be close to zero (as shown in Column 2). In Column 3, I consider country-specific life expectancy at birth, which enters positively but is not statistically significant. In both specifications the main coefficients retain their magnitude and significance levels.

Central bank asset purchases that depress yields on government bonds could be an additional confounding factor. To account for this, I include the domestic central bank's balance sheet size, scaled by GDP, in the regression in Column 4. Reassuringly, the effect of balance sheet size is estimated around zero while the respective coefficients of RF_{it} and RP_{it} remain negative and statistically significance.

Table 9: Reach for yield robustness

	(1)	(2)	(3)	(4)	(5)
RF_{it}	-0.66***	-0.84***	-0.63***	-0.68***	-0.64***
	(0.16)	(0.17)	(0.18)	(0.17)	(0.15)
RP_{it}	-0.10***	-0.10***	-0.10***	-0.09***	-0.10***
	(0.01)	(0.02)	(0.01)	(0.01)	(0.01)
Log assets$_{it-1}$	-0.18				
	(0.91)				
Retired share$_{it-1}$		0.03			
		(0.03)			
Life expectancy$_{it-1}$			0.12		
			(0.35)		
CB assets/GDP$_{it-1}$				0.01	
				(0.01)	
Equity regulation$_{it-1}$					0.01
					(0.02)
Constant	2.25	3.22***	-7.73	2.62**	3.76**
	(2.83)	(1.00)	(27.51)	(1.06)	(1.88)
Observations	1,829	1,249	1,830	1,814	1,810
Funds	105	78	105	105	105
R^2	0.14	0.15	0.14	0.14	0.15
Fund & Time FE	Yes	Yes	Yes	Yes	Yes

Notes: The dependent variable is the active change in the share of risky assets of fund i during year t. Log assets$_{it-1}$ denotes fund i's balance sheet in US dollars at the beginning of year t, expressed in logs. Retired share$_{it-1}$ is the share of a fund's retired to total members, Life expectancy$_{it-1}$ is the expected age in the domestic country at birth retrieved from the World Bank. Equity regulation$_{it-1}$ is the threshold for equity investments specific to pension funds in a country, collected from the OECD. CB assets/GDP$_{it-1}$ is a country's domestic central bank balance sheet size, scaled by the domestic GDP compiled from FRED and national central banks. All regressions include robust standard errors clustered on fund. Significance levels denoted by *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

An additional concern is that the latter half of the sample coincides with a period of de-regulation of financial market participants including pension funds. To address this, I include a country-level proxy for the regulation of pension funds' equity investments retrieved from the OECD, in the regression. Intuitively, it may restrict funds in a particular country to allocating no more than 80% of their balance sheet towards equity investments. Column 5 of Table 9 shows that the effect of the regulation proxy on fund risk-taking. The effect is estimated around zero and does not exceed its standard errors, while the coefficients of the risk-free rate and risk premium remain almost unchanged.

6 Conclusion

What is the effect of low interest rates on financial risk-taking by pension funds? Does it promote reach for yield and investments in riskier assets? Based on a novel and representative database of individual pension funds, this paper documents a sizable increase in the riskiness of pension funds' balance sheets over the recent period. This can be partly explained by funds strategically shifting to riskier asset classes when interest rates fall.

After controlling for risk premia and including fund and year fixed effects, I estimate that a 1 percentage point decrease in the risk-free rate is associated with a 0.66 percentage point increase in the exposure of pension funds to risky assets, after accounting for valuation effects. The results are robust to various robustness checks that isolate exogenous changes in risk-free rates, and are in line with prior studies that document reach for yield by institutional investors in response to low interest rates.

I find that not all pension funds increase their risk-taking when interest rates fall. Specifically, funds with initial excess capacity, that are less underfunded or hold fewer risky assets, are more likely to engage in reach for yield. The effect is also more pronounced during periods of very low interest rates. As a consequence, European pension funds in the sample reach for yield more aggressively compared to their non-European counterparts, particularly in the aftermath of the 2008 financial crisis.

References

Altavilla, Carlo, Luca Brugnolini, Refet S Gürkaynak, Roberto Motto, and Giuseppe Ragusa. 2019. "Measuring euro area monetary policy." *Journal of Monetary Economics* 108:162–179.

Ammer, John, Stijn Claessens, Alexandra Tabova, and Caleb Wroblewski. 2019. "Home country interest rates and international investment in US bonds." *Journal of International Money and Finance* 95:212–227.

Andonov, Aleksandar, Rob Bauer, and Martijn Cremers. 2012. "Can large pension funds beat the market? Asset Allocation, Market Timing, Security Selection and the Limits of Liquidity." *mimeo.*

———. 2017. "Pension fund asset allocation and liability discount rates." *The Review of Financial Studies* 30 (8): 2555–2595.

Andonov, Aleksandar, and Joshua D Rauh. 2022. "The return expectations of public pension funds." *The Review of Financial Studies* 35 (8): 3777–3822.

Antolin, Pablo. 2008. "Pension fund performance." *OECD Working Papers on Insurance and Private Pensions No. 20.*

Autrup, Søren Lejsgaard, and Jakob Roager Jensen. 2021. "QE in a quasi-preferred habitat: The case of the Danish pension sector and the ECB asset purchase programme." *Danmarks Nationalbank Working Papers No. 167.*

Becker, Bo, and Victoria Ivashina. 2015. "Reaching for yield in the bond market." *The Journal of Finance* 70 (5): 1863–1902.

Bergant, Katharina, and Martin Schmitz. 2019. "Valuation effects and international capital flows: Security-level evidence from euro area investors." *mimeo.*

Bergstresser, Daniel, Mihir Desai, and Joshua Rauh. 2006. "Earnings manipulation, pension assumptions, and managerial investment decisions." *The Quarterly Journal of Economics* 121 (1): 157–195.

Bikker, Jacob A, Dirk WGA Broeders, and Jan De Dreu. 2010. "Stock market performance and pension fund investment policy: rebalancing, free float, or market timing." *International Journal of Central Banking* 6 (2): 53–79.

Bohn, Henning, and Linda L Tesar. 1996. "US equity investment in foreign markets: portfolio rebalancing or return chasing?" *American Economic Review* 86 (2): 77–81.

Brennan, Michael J, and H Henry Cao. 1997. "International portfolio investment flows." *The Journal of Finance* 52 (5): 1851–1880.

Calvet, Laurent E, John Y Campbell, and Paolo Sodini. 2009. "Fight or flight? Portfolio rebalancing by individual investors." *The Quarterly Journal of Economics* 124 (1): 301–348.

Camanho, Nelson, Harald Hau, and Hélene Rey. 2022. "Global portfolio rebalancing and exchange rates." *The Review of Financial Studies* 35 (11): 5228–5274.

Campbell, John Y, and Roman Sigalov. 2022. "Portfolio choice with sustainable spending: A model of reaching for yield." *Journal of Financial Economics* 143 (1): 188–206.

Chodorow-Reich, Gabriel. 2014. "Effects of unconventional monetary policy on financial institutions." *NBER Working Paper No. 20230.*

Choi, Jaewon, and Mathias Kronlund. 2018. "Reaching for yield in corporate bond mutual funds." *The Review of Financial Studies* 31 (5): 1930–1965.

Di Maggio, Marco, and Marcin Kacperczyk. 2017. "The unintended consequences of the zero lower bound policy." *Journal of Financial Economics* 123 (1): 59–80.

Domanski, Dietrich, Hyun Song Shin, and Vladyslav Sushko. 2017. "The hunt for duration: not waving but drowning?" *IMF Economic Review* 65 (1): 113–153.

Ellul, Andrew, Chotibhak Jotikasthira, Anastasia V Kartasheva, Christian T Lundblad, and Wolf Wagner. 2021. "Insurers as asset managers and systemic risk." *Kelley School of Business Research Paper*, no. 18-4:18–18.

French, Kenneth R. 2008. "Presidential address: The cost of active investing." *The Journal of Finance* 63 (4): 1537–1573.

Gilchrist, Simon, and Egon Zakrajšek. 2012. "Credit spreads and business cycle fluctuations." *American Economic Review* 102 (4): 1692–1720.

Greenwood, Robin M, and Annette Vissing-Jorgensen. 2018. "The impact of pensions and insurance on global yield curves." *Harvard Business School Finance Working Paper*, no. 18-109:19–59.

Handley, Kyle, and J Frank Li. 2020. "Measuring the effects of firm uncertainty on economic activity: New evidence from one million documents." *NBER Working Paper No. 27896.*

Harvey, Campbell R. 1991. "The world price of covariance risk." *The Journal of Finance* 46 (1): 111–157.

Hassan, Tarek A, Stephan Hollander, Laurence van Lent, and Ahmed Tahoun. 2019. "Firm-level political risk: Measurement and effects." *The Quarterly Journal of Economics* 134 (4): 2135–2202.

Hau, Harald, and Sandy Lai. 2016. "Asset allocation and monetary policy: Evidence from the eurozone." *Journal of Financial Economics* 120 (2): 309–329.

Hau, Harald, and Helene Rey. 2008. "Global portfolio rebalancing under the microscope." *NBER Working Paper No. 14165.*

Heider, Florian, Farzad Saidi, and Glenn Schepens. 2019. "Life below zero: Bank lending under negative policy rates." *The Review of Financial Studies* 32 (10): 3728–3761.

IMF. 2019. "Institutional Investors: Falling Rates, Rising Risks." In *Global Financial Stability Report.*

Ioannidou, Vasso, Steven Ongena, and José-Luis Peydró. 2015. "Monetary policy, risk-taking, and pricing: Evidence from a quasi-natural experiment." *Review of Finance* 19 (1): 95–144.

Ivashina, Victoria, and Josh Lerner. 2018. "Looking for Alternatives: Pension Investments around the World, 2008 to 2017." *mimeo.*

Jarociński, Marek, and Peter Karadi. 2020. "Deconstructing monetary policy surprises—the role of information shocks." *American Economic Journal: Macroeconomics* 12 (2): 1–43.

Lian, Chen, Yueran Ma, and Carmen Wang. 2019. "Low interest rates and risk-taking: Evidence from individual investment decisions." *The Review of Financial Studies* 32 (6): 2107–2148.

Lu, Lina, Matthew Pritsker, Andrei Zlate, Kenechukwu Anadu, and James Bohn. 2019. "Reach for yield by US public pension funds." *Finance and Economics Discussion Series 2019-048.*

Maddaloni, Angela, and José-Luis Peydró. 2011. "Bank risk-taking, securitization, supervision, and low interest rates: Evidence from the Euro-area and the US lending standards." *The Review of Financial Studies* 24 (6): 2121–2165.

Merton, Robert C. 1983. "On the role of social security as a means for efficient risk sharing in an economy where human capital is not tradable." In *Financial Aspects of the United States Pension System*, 325–358. University of Chicago Press.

Mohan, Nancy, and Ting Zhang. 2014. "An analysis of risk-taking behavior for public defined benefit pension plans." *Journal of Banking & Finance* 40:403–419.

Nakamura, Emi, and Jón Steinsson. 2018. "High-frequency identification of monetary non-neutrality: the information effect." *The Quarterly Journal of Economics* 133 (3): 1283–1330.

Novy-Marx, Robert, and Joshua Rauh. 2011. "Public pension promises: how big are they and what are they worth?" *The Journal of Finance* 66 (4): 1211–1249.

Novy-Marx, Robert, and Joshua D Rauh. 2009. "The liabilities and risks of state-sponsored pension plans." *Journal of Economic Perspectives* 23 (4): 191–210.

OECD. 2019. Annual Survey of Investment Regulation of Pension Funds.

Olea, José Luis Montiel, and Carolin Pflueger. 2013. "A robust test for weak instruments." *Journal of Business & Economic Statistics* 31 (3): 358–369.

Ozdagli, Ali K, and Zixuan Kevin Wang. 2019. "Interest Rates and Insurance Company Investment Behavior." *mimeo.*

Rajan, Raghuram G. 2006. "Has finance made the world riskier?" *European Financial Management* 12 (4): 499–533.

Rauh, Joshua D. 2009. "Risk shifting versus risk management: Investment policy in corporate pension plans." *The Review of Financial Studies* 22 (7): 2687–2733.

Rousová, Linda, and Margherita Giuzio. 2019. "Insurers' investment strategies: pro-or countercyclical?" *ECB Working Paper No. 2299.*

Stein, Jeremy C. 2013. "Overheating in credit markets: origins, measurement, and policy responses." *Speech given to the symposium on Restoring Household Financial Stability After the Great Recession, Federal Reserve Bank of St. Louis, St. Louis, Missouri, February*, Volume 7.

Timmer, Yannick. 2018. "Cyclical investment behavior across financial institutions." *Journal of Financial Economics* 129 (2): 268–286.

Watson, Willis Towers. 2019. Thinking Ahead Institute: Global Pension Assets Study 2019.

Wu, Jing Cynthia, and Fan Dora Xia. 2016. "Measuring the macroeconomic impact of monetary policy at the zero lower bound." *Journal of Money, Credit and Banking* 48 (2-3): 253–291.

Appendix A Additional tables and figures

A.1 Alternative risky asset definition

One issue with the measurement of funds' riskiness based on asset classes, adopted from Andonov, Bauer, and Cremers (2017), is varying degrees of risk within asset classes. Especially corporate bonds and loans, classified as risky assets in the main text, could in fact be comparably safe if a fund favors investment grade firms. To address the concern of mis-classification, this appendix presents the main results using an alternative definition.

Formally, I define the risky share of assets, $Share_{it}$, of fund i in year t as the weight of the risky assets relative to the total portfolio,

$$Share_{it} = \frac{Equity_{it} + Alternative_{it}}{Total_{it}} ,$$

where $Equity_{it}$, $Alternative_{it}$ and $Total_{it}$ denote the balances of equities, alternative assets and total assets in fund i's portfolio at the end of year t, respectively.

Based on this alternative classification where only equity and alternative investments are considered risky, I reproduce the main results in Section 5. Table A1 illustrates that reach for yield and risk premium coefficients remain of comparable size and statistical precision compared to the baseline specification, for various risk-free rate proxies. Moreover, the findings remain consistent with the main results when employing monetary policy shocks instead of risk-free rates (see Column 5).

Table A1: Baseline regression, with alternative risky asset definition

	3-month rate	Policy rate	Shadow rate	10-year rate	Policy shocks
	(1)	(2)	(3)	(4)	(5)
RF_{it}	-0.64***	-0.61***	-0.30***	-0.68***	
	(0.15)	(0.15)	(0.08)	(0.24)	
RP_{it}	-0.10***	-0.09***	-0.09***	-0.09***	-0.09***
	(0.01)	(0.01)	(0.02)	(0.01)	(0.02)
$Shock_{it}$					-8.36***
					(3.04)
Constant	1.42	1.20	2.92***	2.01	2.76***
	(1.31)	(1.33)	(0.96)	(1.61)	(0.45)
Observations	1,830	1,828	1,212	1,830	1,110
Funds	105	105	71	105	66
R^2	0.15	0.15	0.17	0.15	0.20
Fund & Year FE	Yes	Yes	Yes	Yes	Yes

Notes: The dependent variable is the active change in the share of risky assets of fund i during year t, where loans and corporate bonds are classified as safe assets. RF_{it} and RP_{it} are the risk-free rate and risk premium, as constructed above, respectively. Column 1 is based on 3-month risk-free rates, columns 2 and 3 use monetary policy rate and shadow rates, respectively. Column 4 is based on 10-year interest rates to proxy risk-free rates. Column 5 uses aggregated monetary policy surprise shock from Nakamura and Steinsson (2018) and Altavilla et al. (2019), respectively. All regressions include robust standard errors clustered on fund. Significance levels denoted by *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

A.2 Risk premium robustness

In this section I show alternative results based on different proxies for the risk premium. One concern is that RP_{it} is inherently not forward-looking and thus unable to capture expectations of fund managers. Although Andonov and Rauh (2022) provide evidence that investment managers frequently extrapolate from past returns, I nonetheless attempt to address this issue.

Table A2 adds a smoothed version of the risk premium that is based on 3-year moving averages (column 2). Compared to RP_{it} the smoothed variable is less volatile and could capture long-term changes to expectations better. The estimates are very close to the original risk premium variable, and the reach for yield coefficient remains of similar size as in the baseline model (column 1).

In column 3, I complement the model with the excess bond premium by Gilchrist and Zakrajšek (2012) as a more forward-looking variable measuring the financial and economic outlook of investors. The coefficient is positive but has large standard errors, suggesting that funds increase risk exposure when the excess bond premium is high. At the same time, the main effects are unchanged compared to the baseline specification.

Table A2: Reach for yield, risk premium robustness

	(1)	(2)	(3)
RF_{it}	-0.66***	-0.47***	-0.70***
	(0.16)	(0.16)	(0.16)
RP_{it}	-0.10***		-0.10***
	(0.01)		(0.01)
$\overline{RP_{it}}$		-0.12***	
		(0.02)	
EBP_{it}			0.85
			(0.83)
Constant	1.43	0.34	0.88
	(1.30)	(1.30)	(1.41)
Observations	1,831	1,831	1,831
Funds	105	105	105
R^2	0.14	0.11	0.12
Fund & Time FE	Yes	Yes	Yes

Notes: The dependent variable is the active change in the share of risky assets of fund i during year t. Column 1 shows the baseline specification, column 2 uses a 3-year smoothed version of the pension fund-specific risk premium, $\overline{RP_{it}}$. EBP_{it} refers to the excess bond premium by Gilchrist and Zakrajšek (2012), retrieved from https://www.federalreserve.gov/econresdata/notes/feds-notes/2016/files/ebpcsv.csv. All regressions include robust standard errors clustered on fund. Significance levels denoted by *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

A.3 Monetary policy surprise robustness

This section contains results based on monetary policy surprises by Jarociński and Karadi (2020). Conceptually their shocks differs from the other monetary policy shocks due to a decomposition of the policy surprise and the market response related to economic outlook. I focus on the former component and follow the same steps as in Table 5.

Reassuringly, the estimates are consistent with the findings based on the policy surprises by Nakamura and Steinsson (2018) and Altavilla et al. (2019). Column 1 of Table A3 highlights that both coefficients remain of similar size and statistical significance compared to the other policy shocks. If anything, the reach for yield coefficient is slightly larger across specifications, also when excluding Asian pension funds (column 2). Quantitatively, a negative shock of one standard deviation is associated with a 0.82 increase in the risky asset share (namely, 0.144 $\times$ -5.714). Once I limit the sample only to countries that are directly affected by the monetary policy shocks, the estimates more than and increase in precision (column 3).

Table A3: Reach for yield with monetary policy surprises

	All countries	Excl. Asia	USA, Euro area
	(1)	(2)	(3)
$Shock_{it}$	-5.71***	-5.77***	-10.21***
	(1.70)	(1.71)	(2.73)
RP_{it}	-0.09***	-0.09***	-0.09***
	(0.01)	(0.01)	(0.02)
Constant	-1.88**	-1.93**	-1.59***
	(0.94)	(0.94)	(0.17)
Observations	1,459	1,433	905
Funds	105	102	66
R^2	0.15	0.15	0.21
Fund & Time FE	Yes	Yes	Yes

Notes: The dependent variable is the active change in the share of risky assets of fund i during year t. $Shock_{it}$ is the aggregated monetary policy surprise shock from Jarociński and Karadi (2020) for the US and Euro area, respectively. Column 1 uses funds from all countries. Columns 2–3 exclude Japanese and South Korean, as well as UK, Swiss, Canadian, Norwegian and Swedish pension funds, respectively. RP_{it} is the risk premium, as constructed above. All regressions include robust standard errors clustered on fund. Significance levels denoted by *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

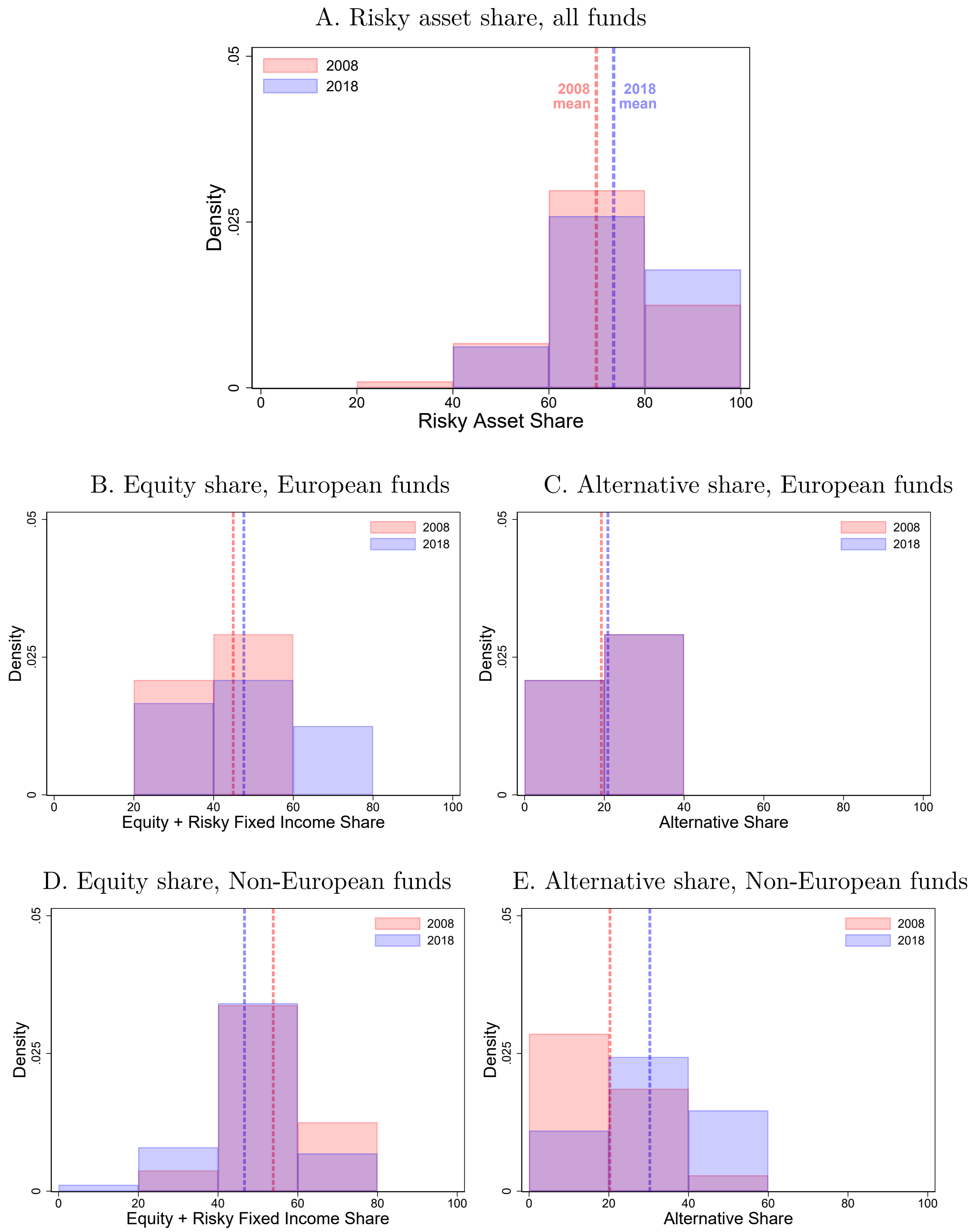
A.4 Risky asset exposure based on target weights

As an additional measure of pension fund decisions to take risk I use strategic (target) asset allocations (see Andonov, Bauer, and Cremers 2017). Target allocations arguably better reflect pension funds decisions to hold risky asset on their balance sheet, because they are not driven by market movements. I collect data for a subset of 56 pension funds that report on target allocations (12 from Europe, 44 from North America and Asia).

Panel A of Figure A1 replicates Figure 1, based on the target allocation. It shows a similar rightward shift of the risky asset distribution after 2008. On average, pension funds increase their target allocations by 5 percentage points, in line with the actual allocations. However, the average level of risky assets is about 10 percentage points higher compared to the actual allocations in Figure 1, potentially driven by the focus on a subsample of funds.

Panels B and C focus on European funds, distinguishing between alternative assets and equity and risky fixed income assets. Panels D and E repeat the same exercise for the subset of non-European pension funds. For the former group of pension plans, the increase in the target risky asset share is driven by equity and risky fixed income, as opposed to alternative assets. Conversely, for North American and Asian funds the increase is entirely driven by alternative assets. Indeed, the share of equity and risky fixed income shows a marked decline during the same period. Overall, this confirms the patterns displayed in Figure 1.

Figure A1: Risky asset shares based on targets, 2008-2018



Notes: This figure shows the cross-sectional distribution of the risky asset share across funds in 2008 (red) and 2018 (blue), based on funds' reported target allocations. Dashed lines denote the respective sample means. Panel A is based on the risky asset share and includes all funds with available data. Panels B-C include only European funds and separately show the alternative and equity share. Similar distributions for Non-European pension funds are contained in panels D-E.

A.5 Size-weighted regressions

Fund size varies significantly in the database. To control for smaller pension funds driving the results, this section presents regressions that are weighted by a pension funds' size, measured through its (average) total assets. Reassuringly, the estimates remain of comparable size and statistical significance (see Table A4).

Table A4: Size-weighted baseline regression

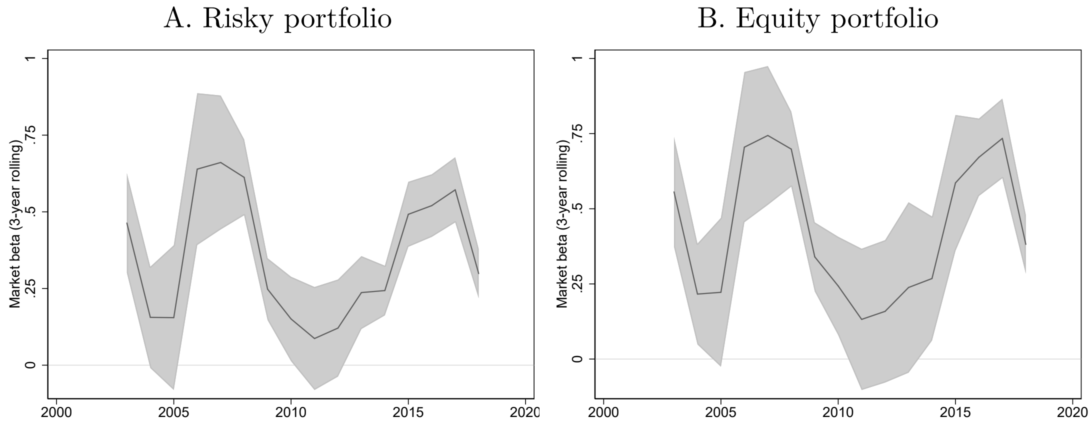
	3-month rate	Policy rate	Shadow rate	10-year rate
	(1)	(2)	(3)	(4)
RF_{it}	-0.50**	-0.46**	-0.20**	-0.63*
	(0.21)	(0.22)	(0.10)	(0.36)
RP_{it}	-0.08***	-0.08***	-0.06**	-0.08***
	(0.02)	(0.02)	(0.02)	(0.02)
Constant	1.42	1.10	2.11**	2.24
	(1.05)	(1.06)	(0.81)	(1.91)
Observations	1838	1836	1219	1838
Funds	105	105	71	105
R^2	0.11	0.11	0.13	0.11
Fund FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes

Notes: The dependent variable is the active change in the share of risky assets of fund i during year t. RF_{it} and RP_{it} are the risk-free rate and risk premium, as constructed above, respectively. Column 1 is based on 3-month interbank rates, columns 2 and 3 use monetary policy rate and shadow rates, respectively. Column 4 is based on 10-year interest rates to proxy risk-free rates. All regressions are weighted by a funds' size measured through total assets. Standard errors are robust and clustered on fund. Significance levels denoted by *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

A.6 Rolling-window β estimates of the risky portfolio

To assess the riskiness within the portfolio of equities and alternative investments, this section provides estimates of the market β, using the MSCI World index as a benchmark. The estimates are computed on a rolling basis over a 3-year period based on annual data. Figure A2 illustrates the path of β for the average fund (including 90% confidence bands), estimated separately for the risky and equity portfolios.

Figure A2: β estimates, 3-year rolling window



Notes: This figure shows the estimates of the market β, based on annual return data from the pension fund database and the MSCI World index. Estimates are illustrated for the average fund, shaded gray bounds denote 90% confidence bands. Panel A is based on the total risky portfolio, panel B uses the equity portfolio.

Appendix B Data and sources

This appendix outlines the methodology to assemble the novel pension fund database. The main reference database on pension fund investment is the Public Plans Database (PPD)[17], covering public pension plans in the United States (see e.g. Mohan and Zhang 2014). To harmonize and allow cross-country comparison I try to follow similar procedures to assemble data for European, Canadian and Asian pension funds. Specifically I collect data on financial information from funds disclosed annual reports, available on the internet.

The first step in this process is to identify a sample of large pension funds from the main advanced economies. To that end I consulted the annual Willis Towers Watson Global Top 300 pension fund ranking, which lists the largest pension funds by asset size in the world.[18] For Germany and Switzerland I also included smaller pension funds to ensure a sufficiently large sample size. Focusing on the Top 300 has the drawback of narrowing the sample to larger funds, which nonetheless might be representative of the industry at large.

[17] See https://publicplansdata.org/.

[18] See https://www.thinkingaheadinstitute.org/research-papers/the-worlds-largest-pension-funds-2020/.

Conveniently, a lot of the US-based pension funds in the top 300 list are already included in the PPD. I retrieve their data and complement it with additional information not contained in the database but in the respective annual reports, for instance on the exchange rate exposure.

For funds domiciled outside of the US, I proceed as follows: First, I systematically search their respective websites for annual reports going back to the year 2000. Most pension funds either list the reports on-line, or provide them upon request. In a few instances I used secondary sources on historical annual reports or regulatory disclosures, e.g. the Bundesanzeiger (Germany) and Yumpu (open source repository for past annual reports). The main constraint to data availability irregular reporting prior to 2008, resulting in an unbalanced panel before that time. Pension funds that do not report data on more than 10 years are excluded from the database.

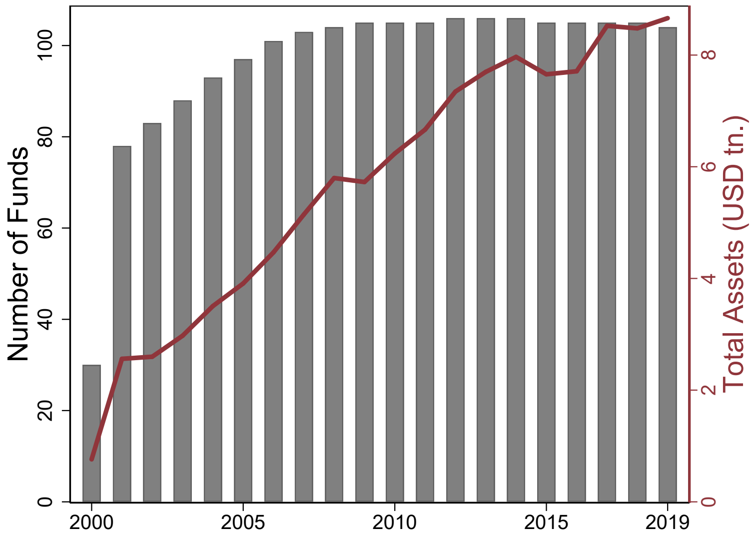
Based on the annual reports, I extract the relevant financial data following the same procedure as in the PPD. Differences in reporting and accounting standards make this exercise challenging. As a result, the main focus is on balance sheet items and detailed financial data, specifically holdings and rates of return broken down by asset class. The database also includes a set of fund-level covariates that are included in the reports, albeit not for the entire sample.

I ensure the data are accurate and broadly representative by bench-marking my sample against established sources, such as the Willis Tower Watson global pension asset study. For the year 2018 the database contains 8.4 trillion US dollars in total holdings, covering roughly 25% of the total pension fund assets in the countries included in the sample (see Table 1).

To illustrate the coverage and asset volume contained in the database, Figure B1 shows the number of funds (gray bars) and total assets in trillion US dollars (red line) in each year. Starting in 2000 only 30 funds are contained in the database, but coverage increases quickly to about 80 funds in 2001, and roughly 100 funds by 2005. Thereafter, the number of funds varies little, with very limited sample attrition. The total assets in the database increase approximately linearly over the sample span, starting at more than 2 trillion in 2001. In 2014 the database encompasses just under 8 trillion US dollars, in recent years asset growth has flattened. As expected, during times of crisis, e.g. in 2008/09 and 2015/2016 pension fund assets did not expand at a similar rate.

For reference, Table B1 lists the individual pension funds covered by the database. It highlights the substantial coverage across countries. Moreover, it shows that the sample is dominated by defined benefit plans, whereas only 8 funds are classified as defined contribution. Many funds, particularly domiciled in Europe, are classified as "hybrid", with both defined benefit and defined contribution components.

Figure B1: Fund coverage and AUM, 2000-2019



Notes: This figure illustrates the sample coverage of the new database. The gray bars (left scale) denote the number of funds included in the sample in each year. The red line (right scale) gives the total assets aggregated over all funds with data, denominated in trillion US dollars.

Table B1: List of pension funds

Pension fund	Country	Type	Pension fund	Country	Type
ABP	Netherlands	DB	Mississippi PERS	USA	DB
Ärzteversorgung Niedersachsen	Germany	hybrid	Missouri Teachers	USA	DB
Versorgungswerk Architektenkammer NRW	Germany	hybrid	National Pension Service	Korea	DB
AMF	Sweden	hybrid	NY State & Local ERS	USA	DB
AP Fonden 1	Sweden	hybrid	Nevada Regular Employees	USA	DB
AP Fonden 2	Sweden	hybrid	New Jersey PERS	USA	DB
AP Fonden 3	Sweden	hybrid	New York City ERS	USA	DB
AP Fonden 4	Sweden	hybrid	North Carolina Local Government	USA	DB
Alabama Teachers	USA	DB	OPSEU	Canada	DB
Alaska PERS	USA	DB	Ohio PERS	USA	DB
Allianz	Germany	hybrid	Ohio Teachers	USA	DB
Arizona SRS	USA	DB	Ontario Pension Board	Canada	DB
Arkansas PERS	USA	DB	Ontario Teachers	Canada	DB
BBC	United Kingdom	DB	Oregon PERS	USA	DB
BC Municipal	Canada	DB	Pension Danmark	Denmark	DC
Personalvorsorge Zürich	Switzerland	DC	PFA	Denmark	DC
Bayerische Versorgungskammer	Germany	hybrid	PFZW	Netherlands	DB
Versicherungsverein des Bankgewerbes	Germany	hybrid	PGB	Netherlands	DB
Bayer	Germany	hybrid	PKA	Denmark	hybrid
CARAC	France	DB	Pensionskasse Basel-Stadt	Switzerland	DC
CDPQ	Canada	DB	Public Sector Pension Investment	Canada	DB
California PERF	USA	DB	Pennsylvania School Employees	USA	DB
California Teachers	USA	DB	Pennsylvania State ERS	USA	DB
Canada Post	Canada	hybrid	Post	Switzerland	hybrid
Canadian Pension Plan	Canada	DB	Publica	Switzerland	DC
Colorado State	USA	DB	RAFP	France	DB
Compenswiss	Switzerland	DC	Railways	United Kingdom	DB
Detailhandel	Netherlands	DB	SBB	Switzerland	hybrid
French Reserve Fund	France	hybrid	SPFO	United Kingdom	DB
Folketrygdfondet	Norway	DB	Saskatchewan Pension Plan	Canada	DC
Florida RS	USA	DB	SYPA	United Kingdom	DB
GMPF	United Kingdom	DB	Sampension	Denmark	DB
Government Pension Fund	Norway	DB	Shell	Netherlands	DB
Government Pension Investment Fund	Japan	DB	South Carolina RS	USA	DB
Georgia Teachers	USA	DB	TFL	United Kingdom	DB
Healthcare of Ontario	Canada	DB	TN State and Teachers	USA	DB
ING	Netherlands	DB	TWPF	United Kingdom	DB
Industriens Pension	Denmark	DB	Texas ERS	USA	DB
Illinois SERS	USA	DB	Texas Teachers	USA	DB
Illinois Teachers	USA	DB	USS	United Kingdom	hybrid
Illmarinen	Finland	DC	Unilever	United Kingdom	DB
Inarcassa	Italy	hybrid	University of California	USA	DB
Iowa PERS	USA	DB	Utah Noncontributory	USA	DB
LA County ERS	USA	DB	Versorgungsanstalt Bund und Länder	Germany	hybrid
PAL	Japan	DB	VER	Finland	DB
Laegernes Pension	Denmark	DB	Varma	Finland	DB
MAPrim	USA	DB	Vervoer	Netherlands	DB
MP Pension	Denmark	DB	Virginia RS	USA	DB
Maryland PERS	USA	DB	WMPF	United Kingdom	DB
Merseyside	United Kingdom	DB	WYPF	United Kingdom	DB
Michigan SERS	USA	DB	Washington PERS 2/3	USA	DB
Migros	Switzerland	DB	Wisconsin RS	USA	DB
Minnesota GERF	USA	DB			

Notes: This table lists the pension funds encompassed in the database, by country of origin and type. The latter category distinguishes funds between defined benefit ("DB") and defined contribution ("DC"), with funds with significant shares of both classified as "hybrid".