Pension Funds and Drivers of Heterogeneous Investment Strategies*

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Abstract

We find remarkable heterogeneity in the investment strategies of pension funds with similar objectives. We use bias-free data to measure their investment strategies through factor exposures within equity and fixed income portfolios. Consistent with our model we find that the funding ratio, risk aversion, and liability duration partially explain heterogeneity in factor exposures. The remaining heterogeneity reflects an annual expected return difference of 0.70-1.50 percentage points that we attribute to differences in beliefs that pension funds reveal through contracting asset management firms. This finding shows that beliefs have important economic implications for beneficiaries who cannot freely choose a pension fund.

Keywords: factor exposures, liabilities, pension funds, portfolio choice, retirement income.
JEL classifications: G11, G23

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I. Introduction

Defined-benefit pension funds play a pivotal role in society as many people depend on them for their retirement savings and investments. Globally, 50 percent of all occupational retirement savings is in defined-benefit pension funds (Willis Towers Watson 2019). The investments of these pension funds serve a similar objective, namely to finance the future liabilities towards their beneficiaries. Therefore, understanding what drives pension funds to structure their investments in a particular way is important. Even small differences in investment strategies may lead to large divergences in performance across pension funds over time. Consequently, these divergences may have a substantial impact on beneficiaries' purchasing power.[1] This is particularly relevant because beneficiaries are typically not free to choose their own pension fund because it "comes with the job". Neither can beneficiaries make individual investment decisions within a defined-benefit pension fund. As a result, these pension funds operate in an environment where they do not have to compete for market share as many other institutional investors do, such as mutual funds.

Despite their pivotal role in society, so far only a few studies have analysed the investment strategies of pension funds. The lack of access to comprehensive and detailed data on this type of investor is the main reason for the limited number of studies. Exceptions are Rauh (2009) and Andonov et al. (2017) who study the effects of regulatory incentives on risky asset allocations for US corporate and public pension plans respectively as well as Anantharaman and Lee (2014) who link risky asset allocations to the compensation incentives of the top management in US corporate pension plans.[2] Our approach differs from these studies because we do not focus on regulatory or compensation incentives.

The primary objective of our study is to measure the heterogeneity in investment

[1] In a defined benefit pension plan, benefits are determined by a formula that takes into account an employee's salary and years of service. Many defined benefit plans, however, also contain elements that depend on the investment returns, such as the cost-of-living adjustment or indexation.

[2] Lakonishok et al. (1992), Blake et al. (1999), Del Guercio and Tkac (2002), Tonks (2005), Goyal and Wahal (2008), and Blake et al. (2013) also examine the investment decisions of pension assets, but the focus in these studies is on the asset managers hired by the pension funds.

strategies across pension funds, the drivers of this heterogeneity, and the effects it has on expected retirement income. We start with a model that solves a mean-variance optimization problem of assets minus liabilities and show that the following characteristics affect the investment decisions of pension funds: liability duration, funding ratio, and risk aversion. In addition to the model, we show that institutional factors, in particular the pension fund's size and type, influence the investment strategies. Nonetheless, these characteristics only explain 36 percent of the heterogeneity in the average returns across pension funds. The heterogeneity that remains reflects an economically sizeable difference in average annual returns of 0.70-1.50 percentage points between the pension funds with the highest and those with the lowest factor exposures. This is equivalent to a difference in expected retirement income of 16-32 percent over a 40-year accrual phase or to an increase in contributions of 19-46 percent to receive the same retirement income. We show that these differences reflect heterogeneity in beliefs across pension funds that they partially reveal through their choices of the asset management firms that they hire to execute their investment strategies. Our findings are remarkable, because the pension funds in our sample have similar investment objectives, yet even after controlling for differences in their characteristics they make distinct investment decisions.

The object of our study is occupational defined-benefit pension funds in the Netherlands. The Dutch occupational pension system is economically important because it is large in terms of total assets under management (AUM). In 2018, the AUM equaled approximately 1.4 trillion euros, and the Dutch system represented 53 percent of the total assets of pension funds in the euro area, (OECD 2019).[3] The proprietary data that we use are the quarterly returns of asset classes over the period from 1999 to 2017, and the return computations are based on the Global Investment Performance Standards (GIPS) as of 2010. The reporting requirements are mandatory, and the data are therefore free from self-reporting biases.

We study investment strategies through factor exposures. Traditionally, the investment

[3]See the infographic in the Internet Appendix (Figure 2).

strategies of pension funds focus on the optimal asset allocations to stocks, bonds, real estate, and alternative assets (e.g. Campbell and Viceira 2002). However, the rise of the global factor literature enables a more granular study of investment strategies within and across asset classes. This literature shows that factors based on a particular signal perform robustly across countries and asset classes. Prime examples include momentum and value (Asness et al. 2013), low beta (Frazzini and Pedersen 2014), and carry (Koijen et al. 2018). We use the existing global factors for equities: the market, value, momentum, carry, and low beta. For fixed income, we construct European factors as the pension funds in our sample primarily invest in euro-dominated bonds, which confirms the currency bias in Maggiori et al. (2020). The market factor consists of investment-grade bonds. Next to the market factor and a credit factor for fixed income, we again use value, momentum, carry, and low beta factors. With the exception of the market and the credit factors, we refer to factors as long-short factors.

We analyze the heterogeneity in investment strategies in the following three steps: first, we measure factor exposures and estimate the cross-sectional average and heterogeneity in factor exposures for both equity and fixed income portfolios; second, we identify the drivers of factor exposures; and third, we measure the differences in the implied beliefs on factor returns. Along these lines we report the following key results.

First, we show that the average pension fund has a stock market beta lower than one and a fixed income market beta larger than one. Further, for both equities and fixed income the average pension fund has a positive exposure to low beta but a negative exposure to value and carry. We also find substantial heterogeneity in both equity and fixed income factor exposures across pension funds.

Second, we find that pension fund's characteristics drive the heterogeneity in the factor exposures, which follows our theoretical framework. Consistent with the predictions of our model we find that pension funds with a low funding ratio, high risk aversion, and long liability duration have higher exposures to the investment-grade fixed income market factor but lower exposures to the other factors. The pension funds' characteristics explain 50 percent of the heterogeneity in the return contribution of the fixed income market factors, but only 20 percent in case of the long-short factors. Motivated by the academic literature, we also study the effects of institutional factors, in particular the effects of the pension fund's size and type. Size as measured by AUM results in more global investment portfolios but does not have an effect on the exposures to long-short factors. Corporate pension funds follow market benchmarks more closely as opposed to industry-wide or professional group pension funds. However, correcting for these institutional factors does not further reduce the heterogeneity in average returns across pension funds.

Third, we show that the remaining differences in investment strategies can be attributed to differences in the implied beliefs on expected returns. We infer these implied beliefs by using our theoretical framework and show evidence in favor of this conjecture. We then show that the pension funds reveal these differences in beliefs through their choices of asset management firms, at least to a reasonable degree. We assess the effect of newly hired asset management firms and find that these have a statistically and economically sizeable effect on the factor exposures.

Fourth, we show that regulations and in particular the discount rate, affect investment strategies. In 2007 a fixed discount rate of 4 percent was replaced by risk-free market interest rates to determine the present discounted value of accrued benefit obligations. This change in methodology has led pension funds to increase their exposure to the fixed income market index and to low beta factors.

Literature review

Our study contributes to the literature on investment behavior in a regulated environment. Rauh (2009) shows that underfunded corporate defined-benefit pension funds in the US invest less in equities than do overfunded pension funds. The author states that the incentive of risk management to avoid costly financial distress dominates the shifting of risk to the Pension Benefit Guaranty Corporation (PBGC) in pension fund investing. We extend this study by showing that underfunded pension funds take less risk within an asset class. We find that within their fixed income portfolio, underfunded pension funds invest more in investment-grade bonds and take less credit risk. This finding confirms the risk management incentive from Rauh (2009). In the Netherlands, no pension guarantee system exists, but underfunded pension funds may try to shift risks to their sponsors (see Broeders and Chen 2012). Employer representatives on a pension fund board may therefore push for risk reduction to avoid this shift.

Andonov et al. (2017) and Lu et al. (2019) find that US public pension funds increase their risk-taking in financial markets when interest rates are lower, particularly for underfunded pension funds. This increase is a way that these public pension funds can artificially support their funding ratio because they discount pension liabilities against the expected returns on their assets. This incentive is created through the US GASB guidelines. We add to this work by analysing the investment behavior in a regulatory environment in which the liability discount rate is linked to the term structure of market interest rates. This is similar to the regulatory environment for US and Canadian private pension funds, and some European pension funds. Our results are therefore more in line with the investment behavior of German insurance companies that demand more as opposed to less safe long-term bonds when interest rates are low (Domanski et al. 2017).

Greenwood and Vissing-Jorgensen (2018) show that regulatory changes in the liability discount rate that link to market interest rates affect the yield curve due to a shock in demand for long-term bonds from these investors. Our results also support the view that the liability structure shapes pension funds' investment behavior, in particular within fixed income portfolios. Our results show that pension funds prefer safe long-term bonds as well as securities denominated in euros. More importantly, we extend Greenwood and Vissing-Jorgensen (2018) by showing the existence of a large heterogeneity in the demand for safe long-term bonds whereby this demand is larger for pension funds with a low funding ratio, high risk aversion, or long liability duration.

Our study also contributes to the broad literature that assesses the effect of institutional investors on asset prices. For example, Coval and Stafford (2007), Gutierrez and Kelley (2009), and Dasgupta et al. (2011) present evidence that institutional investors contribute to mispricing. In particular, Edelen et al. (2016) find that institutional investors trade contrary to anomalies. Our results support this finding because we find many factor exposures to be negative on average. We conjecture that regulation with respect to the liability discount rate is one driving force behind the preference for assets in the short leg of the anomaly. For instance, the exposure to the fixed income value and carry factors decreased substantially when the fixed liability discount rate was replaced by risk-free market interest rates in 2007. Dutch and German government bonds resemble the risk-free term structure of interest rates better as opposed to Italian and Spanish bonds. Yet, at the same time the former have lower value and carry ranks. These two forces may contribute to a negative exposure to the value and carry factors.

The remainder of the study is organized as follows: Section II provides a model to derive the optimal portfolio weights and factor exposures. A description of the data is given in Section III. In Section IV, we estimate the factor exposures and we analyse their drivers in Section V. In Section VI we identify the pension funds' implied beliefs on factor returns. We show how factor exposures changed when the fixed liability discount rate was replaced by market interest rates in Section VII. Section VIII concludes.

II. Motivating model

In this section, we present a model to derive the factor exposures within asset classes and to explain the heterogeneity across pension funds. Our theoretical framework considers the derivation of factor exposures from the perspective of a pension fund.[4] First, we identify

[4] This framework distinguishes itself from the literature that considers the perspective of an individual life-cycle investor as in, for example, Bodie et al. (1992).

the optimal portfolio weights for a mean-variance investor who optimizes their surplus, that is, the value of assets minus that of the liabilities, subject to borrowing and short-sale constraints. Starting with portfolio weights allows us to closely map the model to the existing mean-variance portfolio theory (Markowitz 1952) and to include borrowing and short-sale constraints that are typically applicable to pension funds. Second, we show the implication of the portfolio weights for factor exposures.

We start with the liability structure. A pension fund i pays benefits $B_{i,t+h}$ to its participants in period $t+h$. These benefits can in practice take any value, but because we only consider defined-benefit pension funds, we assume that benefits are known at time t. This assumption is known as the accumulated benefit obligation (ABO). Dutch pension funds do not guarantee inflation protection and we therefore refrain from indexation policies in our analysis. We also assume that the pension fund has a large enough number of participants such that idiosyncratic longevity risk is fully diversified. The present discounted value of all future benefit payments for pension fund i is given by:

$$L_{i,t} = \int_0^\infty B_{i,t+h} \exp\left(-hr_t^h\right) dh, \tag{1}$$

in which r_t^h is the regulatory discount rate as observed at time t for time-to-maturity h.[5] Regulatory discount rates vary widely across jurisdictions. For instance, under the US Government Accounting Standards Board (GASB) guidelines, public pension funds are partially free to discount their liabilities at the expected rate of return on the assets (Andonov et al. 2017).[6] By contrast, US corporate pension funds use the yield on high-quality corporate bonds. In our case, pension funds in the Netherlands used a fixed discount rate of 4 percent until 2007. However, the regulations introduced in 2007 required Dutch pension funds to use the risk-free term structure of market interest rates based on the euro swap curve as the discount rate. Finance theory argues that risk-free market interest rates are indeed the

[5] Table 12 of the Internet Appendix summarizes the symbols that we use in this study.

[6] New GASB rules distinguish between the discount rate calculations for funded and for unfunded pension funds.

applicable discount for guaranteed pension benefits to exclude arbitrage (e.g. Brown and Wilcox 2009; Novy-Marx and Rauh 2009). The value of the liabilities at time $t+1$ is then follows from:

$$L_{i,t+1} = \left(1 + r^L_{i,t+1}\right) L_{i,t} \approx \left(1 + \psi_{i,t} r^b_{t+1}\right) L_{i,t}, \tag{2}$$

in which $r^L_{i,t+1}$ is the liability return that is approximated by the return on the risk-free bonds traded in the market r^b_{t+1} times $\psi_{i,t}$ that represents the duration of pension liabilities over the duration of those bonds. The value of $\psi_{i,t}$ is typically larger than one because the duration of pension liabilities is larger than the average duration of bonds in the market.[7]

Next, we assume the pension fund has access to M assets, and its wealth evolves as follows:

$$A_{i,t+1} = \left(1 + w'_{i,t} r_{t+1}\right) A_{i,t}, \tag{3}$$

in which $w_{i,t}$ is a vector of portfolio weights that pension fund i chooses at time t, and r_{t+1} is a vector of returns from t to $t+1$. Following Sharpe and Tint (1990) and Hoevenaars et al. (2008), we assume that the pension fund has mean-variance preferences over the value of its assets minus the value of its liabilities, or its surplus. We normalize this surplus by dividing it by the value of assets to get the following optimization problem:

$$\begin{aligned} \max\nolimits_{w_{i,t}} \quad & \mathbb{E}_{i,t}\left[u\left(\frac{A_{i,t+1} - L_{i,t+1}}{A_{i,t}}\right)\right] \\ = \quad & \max_{w_{i,t}} \mathbb{E}_{i,t}\left[\frac{A_{i,t+1} - L_{i,t+1}}{A_{i,t}}\right] - \frac{\gamma_i}{2} \mathrm{Var}_t\left[\frac{A_{i,t+1} - L_{i,t+1}}{A_{i,t}}\right], \end{aligned} \tag{4}$$

subject to

[7] We performed a regression of liability returns on factor exposures and found a regression coefficient of 2.2 on the investment-grade fixed income market returns ($R^2 = 0.76$).

$$w'_{i,t}\iota_M \leq c, \tag{5}$$

$$w_{i,j,t} \geq 0 \ \forall j, \tag{6}$$

in which γ_i captures the pension fund's i time invariant risk aversion parameter, ι_M is a vector of ones with length M, c is a constant that defines the constraint on the sum of the weights where typically $c = 1$ that means the pension fund cannot invest more than its entire wealth, and $w_{i,j,t}$ the weight in asset j where $j = 1, ..., M$. Solving (4) for the portfolio weights $w_{i,t}$ results in (see derivation in Appendix A):

$$w^*_{i,t} = \underbrace{\frac{\mathbb{E}_{i,t}[r_{t+1}] + \lambda_{i,t}\iota_M + \delta_{i,t}}{\gamma_i \text{Var}_t[r_{t+1}]}}_{\text{speculative portfolio}} + \underbrace{\frac{\text{Cov}_t[r^b_{t+1}\iota_M, r_{t+1}]\psi_{i,t}\iota_M}{\text{Var}_t[r_{t+1}]} F^{-1}_{i,t}}_{\text{hedging portfolio}}, \tag{7}$$

with

$$\begin{aligned} w^*_{i,j,t} &\geq 0, \\ \delta_{i,j,t} &\geq 0, \\ \delta_{i,j,t} w^*_{i,j,t} &= 0 \ \forall j. \end{aligned} \tag{8}$$

The subjective expectations of pension fund i about the expected returns is defined by $\mathbb{E}_{i,t}[r_{t+1}]$. Because second moments can be estimated more accurately than first moments (e.g Merton 1980), we assume that the variance and covariance of the returns are common knowledge across pension funds. The funding ratio for pension fund i is defined as $F_{i,t} = \frac{A_{i,t}}{L_{i,t}}$, $\lambda_{i,t}$ is the Lagrange multiplier for the restriction that $w'_{i,t}\iota_M = c$, and $\delta_{i,t}$ consists of the Kuhn-Tucker multipliers for the restriction that the portfolio weights are nonnegative. If the

Lagrange multiplier is binding, then $\lambda_{i,t}$ equals:

$$\lambda_{i,t} = \frac{c - \left(\frac{\mathbb{E}_{i,t}[r_{t+1}]+\delta_{i,t}}{\gamma_i \text{Var}_t[r_{t+1}]}\right)' \iota_M - \left(\frac{\text{Cov}_t[r^b_{t+1}\iota_M, r_{t+1}]\psi_{i,t}\iota_M}{\text{Var}_t[r_{t+1}]} F^{-1}_{i,t}\right)' \iota_M}{\left(\frac{\iota_M}{\gamma_i \text{Var}_t[r_{t+1}]}\right)' \iota_M}. \tag{9}$$

The solution in (7) shows that the optimal portfolio weights consist of the sum of two components: a speculative portfolio and a liability hedge portfolio. The Lagrange multiplier (9) ensures that the speculative demand decreases if the hedging demand increases, and vice versa.

Unfortunately, we do not have full access to the portfolio weights of the individual assets. In our empirical analysis, we therefore choose an alternative approach and measure factor exposures. The exposure of the portfolio return r^P to the return on the k^{th} factor r^k is measured as:

$$\beta^k = \frac{\text{Cov}(r^P, r^k)}{\text{Var}(r^k)}. \tag{10}$$

In case the factors are long-short factors, it can be further decomposed to:

$$\beta^k = \frac{\text{Cov}(r^P, r^{k,L} - r^{k,S})}{\text{Var}(r^{k,L} - r^{k,S})} = \frac{\text{Cov}(r^P, r^{k,L})}{\text{Var}(r^{k,L} - r^{k,S})} - \frac{\text{Cov}(r^P, r^{k,S})}{\text{Var}(r^{k,L} - r^{k,S})}, \tag{11}$$

in which $r^{k,L}$ is the return on the "long leg" of the factor, and $r^{k,S}$ is the return on the "short leg" of the factor. Although the pension fund may be restricted to shorting assets, it can have a positive or a negative exposure to a long-short factor. A positive exposure results from a higher demand for the long leg compared to that for the short leg of the factor, and vice versa. To illustrate this point, assume we have a portfolio consisting of value stocks and growth stocks. The portfolio return equals:

$$r^P = w_V r^V + w_G r^G, \tag{12}$$

in which w_V is the portfolio weight of value stocks and r^V is the corresponding return, and w_G is the portfolio weight of growth stocks and r^G is the corresponding return. In this example, let us assume that the portfolio weight of value stocks exceeds the weight of growth stocks, so that $w_V > w_G$. We now explore the exposure of this portfolio return to the long-short factor return. The return correlation between the value and growth stocks is less than one, that is, $\rho_{V,G} < 1$. For a beta neutral factor, we also know that the volatility of the value stock is approximately equal to that of the growth stocks, that is, $\sigma_V \approx \sigma_G$. This condition results in the following factor exposure:

$$\beta^{V-G} = \frac{\text{Cov}(r^P, r^V - r^G)}{\text{Var}(r^V - r^G)} = \frac{(w_V - w_G)\sigma_V^2(1 - \rho_{V,G})}{\text{Var}(r^V - r^G)} > 0 \tag{13}$$

In other words, a higher portfolio weight for value stocks compared to growth stocks results in a positive factor exposure to value, and vice versa.

A. *Testable implications*

This subsection describes the testable implications that follow from our theoretical framework. To formulate the predictions, we first summarize the data that we use to empirically test the model implications.

In our empirical analysis, we use an investment-grade fixed income market index to represent the return on the set of bonds r^b_{t+1}.[8] Further, we use the following factors for fixed income: credit, value, momentum, carry, and low beta. For equities we use a global market, European market, value, momentum, carry, and low beta factor.

Pension funds report their funding ratio and liability duration. We cannot observe the risk aversion parameter directly, but we conjecture that it will be inversely related to the, so-called “required funding ratio”. This required funding ratio is prescribed by law and is comparable to the solvency requirements for banks and insurance companies. If a bank or an insurance company takes more risk, then it will have a higher capital requirement.

[8] The empirical analysis is robust to including other proxies, such as a 10-year German government bond.

Similarly, pension funds that have a large mismatch between assets and liabilities have a higher required funding ratio. This higher ratio shows a willingness to accept more risk (Broeders et al. 2020). Thus, we propose the following testable hypotheses:

1. *Funding ratio*

   A low funding ratio increases demand for the investment-grade fixed income market factor and decreases the overall demand for other factors, and vice versa.

2. *Risk aversion*

   Pension funds with a low risk aversion have larger exposures to factors other than the investment-grade fixed income market factor, and vice versa. We approximate risk aversion through the inverse of the required funding ratio.

3. *Liability duration*

   Pension funds with a long liability duration have a high exposure to the investment-grade fixed income market factor, but lower overall exposure to the other factors, and vice versa.

III. Data

A. Pension fund returns

For the core of our analysis, we use proprietary quarterly return data on Dutch occupational pension funds from 1999Q1 through 2017Q4. The prudential supervisor in the Netherlands collects these data for regulatory purposes. Pension funds report the return on investments as the time-weighted return that takes into account the buying and selling in the asset class during the quarter. As of 2010, pension funds used standardized principles to compute the returns in accordance with the Global Investment Performance Standards (GIPS). Pension funds separately report the overall portfolio return as well as the returns from the equity and the fixed income portfolios. Total returns are in euros net of transaction costs. The returns of the equity and fixed income portfolios exclude the returns from derivative positions. The sample contains 572 distinct pension funds. We correct for pension funds that report the same returns during consecutive periods. Because these are clearly reporting errors, we replace the unvaried returns with missing values.

We distinguish between three different types of pension funds: corporate pension funds, industry-wide pension funds, and professional-group pension funds. Corporate pension funds execute a pension scheme for a particular company. Industry-wide pension funds organize pensions for a specific industry or sector; for example, for civil servants or for the care and welfare sector. These pension funds are typically mandatory, so the collective labor agreement in this sector prescribes that employers must join this pension fund. Professional-group pension funds provide pensions for a specific profession, such as veterinarians or pharmacists. Although corporate and professional-group pension funds are not mandatory, for historical reasons most employers offer a pension scheme to their employees. The fraction of the labor force that participates in a pension scheme exceeds 90 percent. The number of corporate pension funds in the sample is 474, the total number of industry-wide pension funds equals 88, and the number of professional-group pension funds is 10.

Table 1 shows the time series of total AUM for all Dutch pension funds. The AUM grew by a factor of 2.6 over the sample period. The AUM increases each year with the exceptions of a significant drop during the downturn in the stock market following the burst of the Dot-com bubble in 2002 and following the 2008 financial crisis. A continuous and significant drop in the total number of pension funds occurs during the sample period. In 2000, the total number of pension funds was 676; it lowered to a total of 200 in 2017. This drop is in particular due to a large decrease in the number of small corporate pension funds. Because pension funds cannot go bankrupt, our data does not suffer from a survivorship bias. Instead, for cost-efficiency reasons, small pension funds may decide to discontinue their operations and transfer assets and liabilities to an industry-wide pension fund or an insurance company. Not all pension funds fully report returns each year. The table also shows the AUM of pension funds that fully report returns and are therefore in our sample. These pension funds represent on average 93 percent of the AUM of all Dutch pension funds.

[Place Table 1 about here]

Panel A of Table 2 presents the summary statistics for pension funds' equity and fixed income returns and allocations. We measure excess returns against the 3-month Euribor rate that we get from the website of the Dutch Central Bank. The equally weighted average excess return on equities across pension funds and time equals 4.38 percent per year with a standard deviation of 21.28 percent.[9] The negative skewness indicates the equity return series has relatively strong negative values. The mean excess return on fixed income is 3.89 percent per year with a standard deviation of 10.04 percent. The high kurtosis demonstrates fat tails and that is, as we show later, due to the large cross-sectional variation in interest rate hedges. In our analysis, we use equally weighted returns. However, the fact that the Dutch occupational pension fund sector has a few very large industry-wide pension funds is well known. Therefore, for comparison reasons, Table 2 also presents the value-weighted statistics for returns. The value-weighted mean excess return for equities equals 4.80 and for fixed income it equals 3.73 percent.

Table 2 also presents the strategic allocations to equity and fixed income, the duration of the fixed income portfolio, the funding ratio, the required funding ratio, the liability duration, and the fraction of active participants to total participants (active participants plus retirees). Pension funds invest on average 31 percent in equities and 59 percent in fixed income. The average duration of the fixed income portfolio equals 8.2 years with a substantial standard deviation of 8.7 years that indicates the pension funds vary in the extent to which they hedge interest rate risk with bonds. The funding ratio on average equals 116 percent, and the required funding ratio equals 115 percent. The liability duration on average equals 18.6 years, and the fraction of active participants equals 64 percent. The

[9] We compute the standard deviation by using the law of total variance: $\sigma(r) = \sqrt{\mathbb{E}_i(\text{Var}[r]) + \text{Var}_i(\mathbb{E}[r])}$.

latter indicates that about a third of the participants is in the retirement phase.

[Place Table 2 about here]

B. Factor returns

In this subsection, we turn to the factors that explain the cross-section of returns. To distinguish between market factors and the other factors, we refer to the latter as long-short factors. Although controversy exists regarding whether long-short factor returns are rewards for risk or the result of mispricing, we do not take a stance on the underlying driver of these factor returns. We simply interpret these factors as diversified passive benchmark returns that capture patterns in average returns during the sample period we consider.

For the long-short factors we use the four factors that studies have shown to perform robustly across several asset classes and markets: value, momentum, carry, and low beta. The value factor for equities is a strategy that goes long in value stocks and short in growth stocks. As fixed income generally does not have measures of book value, value bonds are defined as bonds with high positive changes in the 5-year yield or high values for the negative 5-year past returns. Long-term past return measures for value come from de Bondt and Thaler (1985).[10] Momentum is defined in exactly the same way for equities and bonds: the past 12-month cumulative return that excludes the most recent month's return (see, e.g. Jegadeesh and Titman 1993). Carry is defined as an asset's future return that assumes the price remains the same. Equity carry is approximately equal to the expected dividend yield minus the risk-free rate. Bond carry is the return that is earned if the yield curve stays the same over the next time period. Low beta is also similarly defined for stocks and bonds: low exposure to the corresponding market index.

[10] For an extended discussion, see Asness et al. (2013).

1. Equity factors

We use the excess market return, value return, momentum return, carry return, and low beta return as factors that explain the pension funds' equity returns. Dutch pension funds have European as well as global equity holdings. The fraction of the equity portfolio they on average allocate to the euro area is 23 percent over the 2007-2017 period; and although we do not have data on the exposure to the euro area prior to 2007, we expect this fraction to be higher.[11] For instance, Berk and van Binsbergen (2015) show that the fraction of mutual funds that invests internationally has significantly increased over the last decade. We therefore include both global and European indices to define the market returns and to account for the currency bias (Maggiori et al. 2020). For the global market factor, we use the quarterly MSCI World Total Return Index in euros; for the European market factor, we use the Euro Stoxx 50 Total Return Index from Bloomberg in euros.[12]

Given that the majority of equity holdings are global, we use global value factors, global momentum factors, global carry factors, and global low beta factors to analyse the equity returns. We take the returns on the value, momentum, and low beta equity factors from the AQR website. The returns on the carry factor are from Ralph Koijen's website. Following the usual factor definitions, the global value and momentum factors are zero-cost, long-short portfolios in individual stocks in the US, the UK, continental Europe, and Japan (Asness et al. 2013). The data for carry and low beta include individual stocks from the following five regions: North America, the UK, continental Europe, Asia, and Australia.

The value, momentum, carry, and low beta returns are all monthly. To match with the pension funds' return cycle, we convert the monthly returns to quarterly returns by means of compounding. We assume pension funds fully hedge currency exposures and convert all

[11] Data on investments in the euro and non-euro areas are published on the website of DNB: https://statistiek.dnb.nl/en/downloads.

[12] The Euro Stoxx 50 Total Return Index represents the 50 largest and most liquid stocks in the euro area. It comprises Austria, Belgium, Finland, France, Germany, Ireland, Italy, Luxembourg, the Netherlands, Portugal, and Spain. The MCSI World index includes the stocks in the Euro Stoxx 50 index.

dollar returns into euros.[13] The factor returns in euros are the dollar factor returns times the gross return on the exchange rate (Koijen et al. 2018) in which the exchange rate measures the number of euros per dollar. For the summary statistics, we furthermore convert quarterly returns into annual ones.

Panel B of Table 2 contains the summary statistics for the factor returns. Within equities, the low beta factor has the highest annualized return (11.03 percent), while value has the lowest (4.00 percent). Next to the market factors, momentum is the most volatile long-short factor over the sample period.

2. Fixed income factors

Compared to equities, Dutch pension funds invest substantially less globally within their fixed income portfolios. Measured over the period from 2007 through 2017, they invested on average 87 percent of the fixed income portfolio in the euro area.[14] Again, we expect this fraction to be even larger prior to 2007. A currency bias for euro fixed income is logical because pension funds' liabilities are also denominated in euros, and fixed income is mainly used to hedge liabilities. We therefore use European factors for fixed income, as opposed to global factors for equities. Because bond returns are largely explained by duration and credit risk, we use the Bloomberg Barclays Euro Aggregate Bond Index and the Bloomberg Barclays Euro High Yield Index in euros as the market and credit factors respectively.[15] Table 2 shows that both the equally and value-weighted excess fixed income returns of pension funds are above the excess return of the investment-grade fixed income index. Pension funds have an incentive to invest in bonds with a high duration to match

[13] The AQR factors are not currency hedged, while the carry factor is fully hedged. Given that currency only explains a minor part of the returns for equities, our results do not materially change if we assume that the currency exposure is not hedged.

[14] Data on investments in the euro and non-euro areas are published on the website of DNB: https://statistiek.dnb.nl/en/downloads.

[15] The Bloomberg Barclays Euro Aggregate Bond Index is a benchmark that measures the investment-grade, euro-denominated fixed-rate bond market that comprises Treasuries, government-related, corporate, and securitized fixed-rate bonds with issuers in Europe. The Bloomberg Barclays Euro High Yield Index measures the market for non-investment grade, fixed-rate corporate bonds with issuers in Europe.

the high duration of their liabilities. The average duration of the fixed income portfolio equals 8.2 (Table 2). As such, benchmark durations are typically lower than the portfolio duration of pension funds. An upward-sloping term structure of interest rates therefore (in part) explains the higher pension fund returns.

As opposed to global, European fixed income long-short factors are not available, so we construct the value, momentum, carry, and low beta factors following the methods of Asness et al. (2013), Koijen et al. (2018), and Frazzini and Pedersen (2014). As the purpose of this study is to gain an insight into the factor exposures of institutional investors rather than the construction of factor returns themselves, we use the exact definitions of the aforementioned authors. We include the following European countries in constructing our factors: Austria, Belgium, Denmark, Finland, France, Germany, Italy, Netherlands, Norway, Spain, Sweden, Switzerland, and the UK. All these countries have investment-grade ratings over our sample period. In Appendix B, we describe the exact procedure for how we construct the factors. For all three factors, we assume the investor fully hedges currency exposures against the euro. Again, we convert monthly returns to quarterly returns by means of compounding. In the case of fixed income, carry has the highest annualized return (1.84 percent) followed by momentum (1.24 percent) and value (1.17). Low beta has a relative low average return equal to 0.86 percent, which is consistent with the findings in Frazzini and Pedersen (2014) who do not find a significant average return for the global low beta bond factor. Value has the highest standard deviation (5.56 percent) followed by momentum (4.54), carry (4.52), and low beta (4.41). Figure 1 shows the evolution of the long-short fixed income factors over time. The correlation matrix in Table 14 of the Internet Appendix also confirms the well-known stylized fact in the literature of the strikingly high negative correlation between value and momentum for the European fixed income factors (Asness et al. 2013).

[Place Figure 1 about here]

IV. Factor exposures

In this section, we proceed with the estimation of the (unconditional) factor exposures. We follow a three-step approach to account for measurement errors in the factor exposures. We describe this procedure in subsection A. In Subsection B we show the implications of heterogeneity in factor exposures for heterogeneity in average performance across pension funds. Subsection C performs a variance decomposition to quantify how much of the cross-sectional differences in average returns are explained by the factors.

A. Factor exposures

We follow a three-step approach to account for measurement errors in the factor exposures. These measurement errors stem from the infrequent observations of pension fund returns. First, we estimate the factor exposures for equity and fixed income returns separately by using the arbitrage pricing theory (APT) developed by Stephen Ross (Ross 1976). We denote equity by $a = E$ and fixed income by $a = FI$ and measure the factor exposures by regressing the excess returns of pension fund $i = 1, \ldots, N$ for asset class a on the excess factor returns in the following way:

$$r^a_{i,t} - r^f_t = \alpha^a_i + \beta^{a\prime}_i f^a_t + \epsilon^a_{i,t}, \quad \text{for} \quad i = 1, \ldots, N, \tag{14}$$

in which r^f_t is our proxy for the risk-free rate: the Euribor 3-month rate, f^a_t is a vector of factor returns of length K for asset class a, and $\epsilon^a_{i,t}$ is the idiosyncratic error term with standard deviation σ^a_i. For equities, vector f^E_t contains the following six elements: the global excess market return, the European excess market return, the global value stock return, the global momentum stock return, the global carry stock return, and the global low beta stock return. For fixed income, the vector f^{FI}_t has the following six elements: the European excess investment-grade fixed income market return, the European excess high yield fixed income return, the European value fixed income return, the European momentum fixed income return, the European carry fixed income return, and the European low beta fixed income return. In the remainder of the study, we drop the superscript a to simplify the notations. In Table 15 of the Internet Appendix, we present the results of the estimated betas using the time-series OLS in detail.

Second, we use a random-coefficient model to estimate the priors for the factor exposures. The estimated factor exposures that use the time-series OLS suffer from measurement error because we only observe quarterly returns (Merton 1980). The cross-sectional mean and standard deviation may therefore substantially deviate from the true moments. Because the focus is on the cross-sectional mean and standard deviation of factor exposures, we correct for this deviation by using a prior on the mean and the variance in the factor exposures that we derive from a random-coefficients model. Compared to a standard regression model in which the parameters are fixed to a single value, the random-coefficients model allows for cross-sectional variation in the parameters. We specify the random-coefficients model as follows:

$$\begin{aligned} r_{i,t} - r_t^f &= \alpha_i + \beta_i' f_t + \epsilon_{i,t} \\ &= \alpha + \beta' f_t + v_i' f_t + u_i + \epsilon_{i,t}, \end{aligned} \tag{15}$$

in which v_i is a vector of length L that captures all the random-effect coefficients, and $\epsilon_{i,t}$ is the idiosyncratic error term with variance σ_i. Furthermore, we assume that L is equal to the number of factors K; in other words, we allow all factor exposures to vary across pension funds. The exact procedure for estimating the random-coefficients model is in Internet Appendix B. We use the regression coefficients of the random coefficients model as the prior distribution in the analysis. Thus, the prior betas are defined as:

$$\beta_i^k \sim N(\hat{\beta}^k, \hat{\sigma}^2_{\beta^k}) \quad \text{for} \quad k = 1, \ldots, K \quad \text{and} \quad i = 1, \ldots, N, \tag{16}$$

in which $\hat{\beta}^k$ is the fixed-effect estimator, and $\hat{\sigma}^2_{\beta^k}$ is the variance in the random effect from

Equation (15). The variances in the random effects facilitate the testing for the existence of true heterogeneity in the factor exposures. We find significant average factor exposures in both the equity and the fixed income portfolios. Similarly, we also find significant cross-sectional heterogeneity in all factor exposures except for momentum in the fixed income portfolios. The coefficient estimates that include a detailed interpretation appear in the Internet Appendix B.

Third, we derive posterior factor exposures. Following Vasicek (1973), Elton et al. (2003), and Cosemans et al. (2016), we combine the estimated factor exposures from the time-series OLS regressions with the prior to obtain the posterior betas. These exposures are approximately normally distributed with the following mean and variance:

$$\tilde{\beta}_i^k = \frac{\hat{\beta}_i^k / se(\beta_i^k)^2 + \hat{\beta}^k / \hat{\sigma}^2_{\beta^k}}{1/se(\beta_i^k)^2 + 1/\hat{\sigma}^2_{\beta^k}} \quad \text{for} \quad k = 1, \ldots, K \quad \text{and} \quad i = 1, \ldots, N \tag{17}$$

$$\tilde{\sigma}^2_{\beta_i^k} = \frac{1}{1/se(\beta_i^k)^2 + 1/\hat{\sigma}^2_{\beta^k}} \quad \text{for} \quad k = 1, \ldots, K \quad \text{and} \quad i = 1, \ldots, N, \tag{18}$$

in which $\hat{\beta}_i^k$ is the estimated exposure to factor k from the time-series OLS regressions presented in Equation (14) for pension fund i, and $se(\beta_i^k)$ is the corresponding standard error. Equation (17) shows that the factor exposures of pension funds with less precise sample estimates shrink to the prior. The distribution of posterior factor exposures shows the heterogeneity across pension funds corrected for the measurement error. As a result, the posterior betas are economically interpretable.

For equities, Table 3 shows the average exposures to the world and European market factors as equaling 0.67 and 0.27 respectively and with standard deviations equaling 0.18 and 0.15. The sum of the market exposures equals 0.94 that indicates the pension funds, on average, take slightly less systemic risk than the market portfolio. The standard deviations of the posterior market exposures shrink by about one-half compared to the time series regressions that indicates that the substantial variation in the market exposures remains after correcting for the measurement error. The average exposures to value, momentum, carry, and low beta equal −0.05, −0.04, −0.06, and 0.08, respectively. Average negative momentum and value exposures for equities are consistent with recent findings for retail investors in e.g. Luo et al. (2020). The standard deviation in factor exposures for value, momentum, carry, and low beta are 0.07, 0.04, 0.13, and 0.08, respectively. The standard deviation in the posterior factor exposures shrinks by two-thirds for value, five-sixths for momentum, three-fourths for carry, and two-thirds for low beta compared to the time series regressions. A substantial part of the cross-sectional variation in the factor exposures is thus the result of measurement error. Yet, the heterogeneity in the factor exposures remains, especially for value, carry, and low beta.

For fixed income, the average exposure to the investment-grade market factor equals 1.11. A fixed income market beta larger than one is consistent with our model, because the duration of the liabilities is much longer compared to the duration of the bond market index. The cross-sectional standard deviation equals 0.31. The standard deviation of the posterior market exposure shrinks by one-half compared to the time-series regressions that indicates the substantial variation in the market exposures remains after correcting for the measurement error. The average exposures to credit risk, value, momentum, carry, and low beta are 0.02, −0.16, 0.07, −0.07, and 0.21, respectively. The cross-sectional standard deviations of credit, value, carry, and low beta equal 0.06, 0.15, 0.09, and 0.18 respectively. Again, substantial variation in factor exposures from the time series regressions is due to measurement error, although the heterogeneity in the factor exposures remains. Because we are not able to detect any variation in the exposure to momentum (Table 16), all estimates shrink to the mean; and the standard deviations obtained from the time-series regressions are almost all due to measurement error.

[**Place Table 3 about here**]

B. Heterogeneity in average excess returns

The variation in the factor exposures that we observe has consequences for the average excess return differences across pension funds. To determine these differences, we compute the contribution of each of the factors to the average excess returns. We use the posterior betas obtained from Equation (17). The contribution of each of the factors is then computed as:

$$\mathbb{E}(r_i^k) = \tilde{\beta}_i^k \lambda^k \quad \text{for} \quad k = 1, \ldots, K \quad \text{and} \quad i = 1, \ldots, N, \tag{19}$$

in which λ^k is the historical average return for factor k.

The total average excess return for pension fund i equals $\mathbb{E}(r_i^e) = \sum_{k=1}^{K} \tilde{\beta}_i^k \lambda^k$. We rank pension funds based on the total average excess returns from highest to lowest and split them in five equally weighted groups. We then disentangle the contribution of each factor to the average excess returns using (19). Table 4 summarizes the results for equities, fixed income, and the total portfolio level.

For equities, we find that taking all factors together, the contribution of the factor exposures to average excess returns varies between 2.23 and 6.40 percentage points. Pension funds with the highest average excess returns have a return contribution of the market that is equal to 4.60 percentage points, while this return contribution for pension funds with the lowest average excess returns equals 4.11 percentage points. For the long-short factors, the dispersion is much larger for carry and low beta compared to the market. The average return contribution of the carry factor equals 0.44 percentage points at the highest and −1.25 percentage points at the lowest percentiles. For low beta, the return contribution varies between 1.66 and −0.05.

For fixed income, taking both market and long-short factors together, the contribution of the factor exposures vary between 1.91 and 3.95 percentage points. The variation in the contributions of market exposures is larger than for equities and varies between 1.99 and 3.82

percentage points. The long-short factors play a subordinate role. The negative contribution of the long-short factor exposures is due to the typically negative exposure to value and carry factors.

We now turn to the total portfolio level. The average excess return for the total portfolio is computed as the sum of the equity average excess return times the equity weight and the fixed income average excess return times the fixed income weight. All factors taken together, the contribution to the average returns differs by 2.35 percentage points. In other words, pension funds with the highest factor exposures versus pension funds with the lowest factor exposures have a 2.35 percentage point higher average return on the entire portfolio. The contribution of the market factor has values that vary between 2.74 and 4.04 percentage points, and the contribution of the long-short factor exposures has values that vary between -0.53 and 0.51 percentage points.

[Place Table 4 about here]

C. Variance decomposition

Next, we perform a variance decomposition to quantify how much of the cross-sectional differences in average excess returns are explained by the factor exposures. We first calculate the average excess return of each pension fund per asset class using Equation (17):

$$\tilde{\mu}_i = \tilde{\alpha}_i + \tilde{\beta}_i^{\prime}\lambda \quad \text{for} \quad i = 1, \ldots, N, \tag{20}$$

in which λ is a vector of historical average factor returns.

Second, we take the cross-sectional covariance of each side with $\tilde{\mu}$ that is the vector of average excess returns with a length that is equal to N. Because $\text{Cov}(\tilde{\mu}, \tilde{\mu}) = \text{Var}(\tilde{\mu})$, we can divide it by the variance of $\tilde{\mu}$ to get:

$$1 = \frac{\text{Cov}(\tilde{\beta}'\lambda, \tilde{\mu}) + \text{Cov}(\tilde{\alpha}, \tilde{\mu})}{\text{Var}(\tilde{\mu})} = \frac{\sum_{k=1}^{K} \text{Cov}(\tilde{\beta}^{k\prime}\lambda^k, \tilde{\mu}) + \text{Cov}(\tilde{\alpha}, \tilde{\mu})}{\text{Var}(\tilde{\mu})}, \tag{21}$$

in which $\tilde{\mu}$ and $\tilde{\beta}^{k\prime}\lambda^k$ are both vectors of length N.

Table 5 shows the results for both equity and fixed income returns. The exposures to the global and European market returns explain 14.05 and 5.41 percent of the variation in average equity excess returns, respectively. For the long-short factors, the ones with the most explanatory power are carry and low beta, and they respectively explain 40.15 and 41.22 percent of the variation in average excess returns. Value explains 3.67 of the variation in average excess returns and momentum 2.58 percent. This finding is consistent with the highest return contribution heterogeneity found for the carry and low beta factors. Alpha has negative explanatory power for average excess returns, which means that the pension funds with a high alpha have slightly lower average excess returns.

For fixed income, the European investment-grade market return explains 71.32 percent of the variation in average excess returns, and the high yield return explains 2.79 percent. Low beta, value, and carry explain 4.83, 1.53, and 6.48 of the variation in average excess returns. Consistent with the absence of true heterogeneity across momentum exposures, momentum has negligible explanation power. Alpha has positive explanatory power for average excess returns equal to 13.28 percent.

[Place Table 5 about here]

V. Drivers of factor exposures

The previous section shows that there is substantial heterogeneity in the factor exposures across pension funds. In this section, we analyse the drivers behind these factor exposures. We have two groups of drivers. The first group are the pension funds' characteristics from our theoretical framework in Section II. This group includes the funding ratio, risk aversion, and liability duration.[16] The second group consists of institutional factors, in particular the pension fund's size and type.

We perform a panel data regression of the funding ratio, the risk aversion, the liability duration, size, and type that we interact with the factor returns:

$$
\begin{aligned}
r^e_{i,t} &= \delta_0' f_t + \delta_1' f_t \times \mathrm{F}_{i,t-1} + \delta_2' f_t \times \gamma_{i,t-1} + \delta_3' f_t \times \mathrm{D}_{i,t-1} + \delta_4' f_t \times \mathrm{AUM}_{i,t-1} \\
&+ \delta_5' f_t \times \mathrm{Type}_i + \epsilon_{i,t},
\end{aligned} \tag{22}
$$

in which $\mathrm{F}_{i,t-1}$ is the funding ratio of pension fund i at time $t-1$, γ_{it-1} is the risk aversion of pension fund i at time $t-1$, $\mathrm{D}_{i,t-1}$ is the liability duration for pension fund i at time $t-1$, AUM_{it-1} is the AUM for pension fund i at time $t-1$ for the corresponding asset class, and Type_i is the pension fund type. We demean FR_{it-1}, γ_{it-1}, D_{it-1}, and AUM_{it-1} such that δ_0 can be interpreted as the average (industry-wide) pension fund.

A. *Pension funds' characteristics*

1. Funding ratio

Our theoretical framework predicts that pension funds with a low funding ratio should have a high exposure to the fixed income market factor, and vice versa. Moreover, the lower the funding ratio, the less room for the speculative portfolio if the borrowing constraint is binding. Hence, we predict that on average, lower exposures will exist to factors other than the fixed income market factor for pension funds with low funding ratios, and vice versa. For equities, we find that pension funds with a high funding ratio do not have different equity factor exposures (Table 6). For fixed income, we find that pension funds with a high funding ratio have less exposure to the market factor and more exposure to the credit and carry factor. A one standard deviation increase in the funding ratio (0.16) decreases the exposure to the

[16] In this study, we focus on factor exposures. In the Internet Appendix we show that the predictions from our theoretical framework also empirically hold for the allocation to equity and fixed income (Table 17).

market factor by 0.18 and increases the exposure to the credit factor by 0.02 and the carry factor by 0.07. Overall, these findings are consistent with our theoretical framework: pension funds with a low funding ratio invest more in investment-grade fixed income securities that correlate positively with their liabilities, while they have a lower aggregate exposure to the other factors.

Andonov et al. (2017) find the opposite result for US public pension funds. This difference is driven by regulation: The discount rate of US public pension links to the expected returns on assets, while Dutch pension funds have to use a discount rate that links to market interest rates. The incentive to invest in risky assets to artificially improve the funding status of US public pension funds therefore does not apply to Dutch pension funds. A discount rate based on market interest rates is widely used and is the standard for US private pension funds, Canadian, and other European pension funds.

2. Risk aversion

We use the inverse of the required funding ratio as an implicit measure of the risk aversion in which $\gamma \propto 1/\text{RFR}$, as described in Section II. Our theoretical framework predicts that pension funds with a higher risk aversion coefficient should have a higher exposure to the fixed income market factor and lower exposure to the other factors. For equities, an increase of one standard deviation in the proxy for risk aversion (0.04) slightly decreases the exposure to the global market factor by 0.01. For fixed income, a higher risk aversion coefficient increases the exposure to the market factor substantially and the exposure to momentum slightly. An increase of one standard deviation in the implicit risk aversion coefficient increases the exposure to the market factor by 0.39 and to momentum by 0.04. On the other hand, a higher implicit risk aversion coefficient decreases the exposure to the credit factor, value, carry, and low beta. An increase of one standard deviation in the implicit measure of the risk aversion coefficient decreases the exposure to the credit factor by 0.03, value by 0.04, carry by 0.15, and low beta by 0.07. Overall, these findings are consistent with our theoretical framework:

pension funds with a higher risk aversion coefficient have a higher exposure to safe assets and less exposure to assets that are uncorrelated with their liabilities.[17]

3. Liability duration

Our theoretical framework predicts that pension funds with a long liability duration should have a higher exposure to the fixed income market factor and lower exposures to the other factors, and vice versa. For equities, pension funds with a long liability duration have a higher exposure to the global market index that is approximately offset by a lower exposure to the European market index. Moreover, a one standard deviation increase in the liability duration decreases the exposure to low beta by 0.02. For fixed income, pension funds with a long liability duration have a larger exposure to the market factor and a lower exposure to the credit factor. An increase of one standard deviation in the liability duration increases the exposure to the market factor by 0.40 and decreases the exposure to credit by 0.03. Pension funds with a long liability duration also have lower exposure to value and carry. An increase of one standard deviation in the liability duration decreases the exposure to value and carry by 0.05 and 0.14. Again, these findings are consistent with our theoretical framework. We find similar results when using the ratio of active participants relative to the retirees as a proxy for the liability duration (Table 18 in the Internet Appendix).

[Place Table 6 about here]

[17]The relation between the required funding ratio and asset allocation decisions is mechanical: a higher allocation to equities increases the required funding ratio. However, *within* asset classes there is no such relation. Pension funds that for instance invest more in risky equities (i.e., high beta stocks) do not experience a higher required funding ratio.

B. Institutional factors

1. Size

Size might affect market and long-short factor exposures for two competing reasons. First, large pension funds generally have economies of scale and therefore can bring more expertise to their investment process. As a result, we predict that large pension funds will invest in a more globally and sophisticated manner. Second, due to the price effect of large trades – see, for example, Easley and O'Hara (1987) – pension funds with a substantial AUM in a specific asset class are constrained and might choose to implement factor investing on a low scale relative to pension funds with a lower AUM. The results are in Table 7. For equities, size has a positive and significant effect on the exposure to the excess global market return, and a negative and significant effect on the exposure to the excess European market return. A pension fund that is 10 times larger has a 0.06 higher exposure to the global market and a 0.05 lower exposure to the European market. This finding confirms earlier conjectures that large pension funds have the means to diversify their equity investments more globally than small pension funds. Size does not affect the other factor exposures. These results thus do not confirm the conjecture that large pension funds might be constrained in implementing factor strategies.

2. Pension fund type

Differences in the organizational structure across pension funds might also affect factor exposures. One important difference is that listed companies have to report on the status of their pension funds in their own financial disclosures. Also the risk of the pension fund may be reflected in the risk profile of the company (Jin et al. 2006). This is not the case for the sponsors of an industry-wide pension fund or a professional-group pension fund. Corporate pension funds may therefore be less willing to take risk or to deviate from market benchmarks. In Table 7 we use industry-wide pension funds as a reference group. We observe that the only notable difference between corporate pension funds and industry-wide pension funds is that they have a higher exposure to the global market equity index. This is consistent with corporate pension funds following benchmarks more closely as opposed to the industry-wide pension funds.

[Place Table 7 about here]

VI. Heterogeneity in beliefs

So far, we have seen that pension fund's characteristics and institutional factors drive factor exposures. In this section, we first show that these do not fully explain investment strategies and that there still remains significant heterogeneity in the factor exposures. We then explain the remaining heterogeneity from implied beliefs in the factor returns. We also show that these beliefs (partially) reveal themselves via the choice of the asset management firm.

A. Remaining heterogeneity in factor exposures

Consistent with our theoretical framework, the previous section shows that part of the heterogeneity results from differences in the pension fund characteristics. The theoretical framework shows, and the empirical analysis confirms, that the relative weight of the liability hedge portfolio increases if the funding ratio is low, when the risk aversion is high and when the liability duration is long. In this section, we adjust the posterior betas for each pension fund such that the liability hedge demand is equal across pension funds and compute the heterogeneity in performance with the adjusted exposures.

Formally, we adjust the posterior betas of each pension fund as follows:

$$\tilde{\beta}^k_{adj,i} = \tilde{\beta}^k_i - \hat{\delta}^k_1 \times \overline{\mathrm{F}}_i - \hat{\delta}^k_2 \times \overline{\gamma}_i - \hat{\delta}^k_3 \times \overline{\mathrm{D}}_i \quad \text{for} \quad k = 1, \ldots, K \quad \text{and} \quad i = 1, \ldots, N. \tag{23}$$

Because the time series averages $\overline{\mathrm{F}}_i$, $\overline{\gamma}_i$, and $\overline{\mathrm{D}}_i$ are defined relative to the cross-sectional sample average, the adjusted factor exposures decrease for a positive coefficient (i.e. $\hat{\delta}_1^k, \hat{\delta}_2^k, \hat{\delta}_3^k > 0$) when the funding ratio, risk aversion, or liability duration is higher than average, and vice versa. We do the same for the institutional factors. The heterogeneity that remains is unexplained by the pension fund characteristics or institutional drivers.

We redo the analysis from Section IV (subsection B) and Table 8 summarizes the results. In Panel A, we present the unadjusted excess returns. Pension funds with the highest factor exposures versus pension funds with the lowest factor exposures have a higher average return by 2.35 percentage points on the entire portfolio. Of this difference, 1.30 percentage points are driven by market factors and 1.05 by long-short factors. In Panel B, we correct the excess returns for the pension fund characteristics. The return difference between the top and bottom percentiles is 1.50 percentage points. The contribution of the market factors varies from 3.22 to 3.91 percent, and the contribution of long-short factors varies between -0.25 and 0.56 percent. A total return difference of 1.50 percentage points that cannot be explained by the pension fund characteristics is an economically sizable effect. A lower annual return by 1.50 percentage points decreases the expected retirement income by 32 percent over a 40-year accrual phase or increases contributions by 46 percent to get the same income.

The heterogeneity in the average excess returns remains the same in Panel C if we also adjust the factor exposures for institutional factors in the same way as in (23). Because pension funds do not differ substantially in their aggregate equity market exposure, Panels B and C show that the differences in the pension fund characteristics account for roughly 50 percent of the heterogeneity in the return contribution of the fixed income market factors. The pension fund characteristics only explain 20 percent of the heterogeneity in the return contribution of the long-short factors.

Finally, in Panel D we redo the analysis for a subsample of pension funds that are in the sample for at least 24 quarters to further reduce the effect of the measurement error. For this group of pension funds, we find a difference in average excess returns of 1.16

percentage points, and this is equivalent to a difference in expected retirement income of 24 percent. Controversy about the performance of long-short factors exists. However, excluding long-short factors all together, we still find an unexplained difference in the average annual returns of roughly 70 basis points, which is equivalent to a difference in expected retirement income of 16 percent.

[Place Table 8 about here]

B. Implied beliefs on expected factor returns

The substantial heterogeneity in the average excess returns that is left after the correction for differences in the pension fund characteristics and institutional drivers may also indicate that pension funds differ in their beliefs about factor returns, particularly so for equities. To show this heterogeneity we identify the pension funds' unconditional implied beliefs about expected (excess) factor returns. To do so, we apply the method as described in Shumway et al. (2011). In their work, they assume that fund managers choose portfolio weights such that they maximize their expected returns over a benchmark while minimizing the tracking error volatility. They find true beliefs to be:

$$\mu_i \approx \gamma_i \delta_i \Sigma_i (w_i - q_i) - \lambda \mathbf{1} \qquad \text{for} \qquad i = 1, \ldots, N, \tag{24}$$

in which Σ_i is the variance-covariance matrix of returns that is estimated with historical return data and is therefore similar across managers ($\Sigma_i = \Sigma$), w_i are the portfolio weights, q_i are the benchmark portfolio weights, γ_i is the risk aversion parameter of fund manager i, δ_i is the total precision of fund manager i, and λ is the Lagrange multiplier of the borrowing constraint. The total precision parameter measures the informedness of the fund manager about future returns and is the sum of two parts $\delta_i = \tau^{-1} + \tau_i^{-1}$, in which τ^{-1} is the precision of the prior on expected returns, and τ_i^{-1} is the precision of a signal about the expected returns of fund manager i.

The true beliefs are an affine function of the implied beliefs in which the ith fund manager's implied beliefs about the expected returns, $\hat{\mu}_i$, are derived in Shumway et al. (2011) as follows:

$$\hat{\mu}_i = \Sigma_i(w_i - q_i) \qquad \text{for} \qquad i = 1, \ldots, N. \tag{25}$$

We can apply this framework to our model in Section II. Because we cannot observe all the parameters required to identify the true beliefs, we assume reasonable parameter values to get estimates of the implied beliefs on the expected factor returns. The results that follow should therefore be interpreted as approximations of the true beliefs in which we are particularly interested in the magnitude of differences in the expected returns across pension funds.

As in Shumway et al. (2011), to measure implied beliefs, we refrain from private signals and set $\tau_i^{-1} = 0$. We also assume that pension funds have the same overall precision in the prior equal to $\tau = 1$. Together with the assumption of no private signals ($\tau_i^{-1} = 0$), we have $\delta_i = 1$. A precision in the prior equal to $\tau = 1$ means that pension funds have a prior $p(\mu_0)$ that is normally distributed with a mean μ and a variance-covariance Σ, that are, for instance, based on historical returns:

$$p(\mu_0) \sim N(\mu, \Sigma). \tag{26}$$

For the benchmark factor exposures q_i, we assume an exposure of one to the global market factor and a zero exposure for all the other factors for equities. For fixed income, we assume an exposure of one to the investment-grade fixed income market factor and zero to all other factors. These weights corresponds to a passive investor who follows the benchmark exactly.

Using our model in Section II in an unconditional setting and applying the above assumptions to (24), we can derive the implied beliefs about the expected factor returns for pension fund i as:

$$\hat{\mathbb{E}}_i[r_{t+1}] = \gamma_i \text{Var}[r_{t+1}](\beta_i - q_i) - \gamma_i \text{Cov}[r^b_{t+1}\iota_N, r_{t+1}]\psi_i \iota_N F_i^{-1} \qquad \text{for} \qquad i = 1, \ldots, N. \tag{27}$$

As opposed to Shumway et al. (2011), we do not get rid of γ_i when estimating the implied beliefs as we do have information about the risk aversion coefficient of pension funds. Additionally, compared to (25), we correct implied beliefs for the liability hedge demand of pension funds.

As we are interested in the unconditional expectation of returns, we take the average funding ratio over the sample period as the estimate for F_i. We apply the same method for the liability duration and divide it by the typical duration of the fixed income market index of seven years to compute ψ_i. We represent γ_i with $\gamma_i \approx 6 \times \frac{1}{RFR_i}$ in which RFR_i indicates the average required funding ratio for pension fund i. As the average required funding ratio equals 1.15, $\gamma_i = 6 \times \frac{1}{1.15} = 5$ means that there is a risk aversion parameter of five for the average pension fund. Because we are particularly interested in the cross-sectional heterogeneity in implied beliefs across pension funds, the precise magnitude of the average risk aversion coefficient is of less importance.

Table 9 shows the results for the annualized implied beliefs (27) on the expected factor returns and conditional on all pension funds having the same informedness. For equities, a median pension fund has positive implied beliefs about the European market factor (1.10 percentage points), while they are slightly negative for the global market factor (-0.12 percentage points). This is consistent with a home/currency bias to European countries. For value and low beta, pension funds have positive implied beliefs, while they are negative for momentum and carry. The median implied belief for the value factor equals 0.41 percentage points and equals -0.40 percentage points for momentum, -0.21 for carry, and 0.39 for low beta. This belief means that pension funds on average expect a higher return on value and on low beta of 0.80 percentage points compared to momentum. There is substantial heterogeneity in the implied beliefs about the expected factor returns. For instance, the pension funds with the most pessimistic views on value expect a negative return of 0.34 percentage points on top of the benchmark return, while pension funds with the most optimistic views expect a positive return of 1.30 percentage points.

For fixed income, the median implied beliefs on the investment-grade market factor equals -0.03 percentage points. The heterogeneity in the implied beliefs for the market factor is limited and indicates that when correcting for the hedging demand, pension funds disagree far less about the expected returns on the market factor. For the credit factor, the implied beliefs equal on average -0.19 and have substantial heterogeneity across pension funds. They range from -1.18 to 0.49 percentage points. For the value factor, the implied beliefs equal -0.46, 0.28 for momentum, -0.27 for carry, and 0.45 for low beta. The greatest heterogeneity in the implied beliefs on the expected long-short factor returns exists for low beta in which pension funds with the most pessimistic views on low beta expect a return of zero percentage points, while pension funds with the most optimistic views expect a positive return of 0.81 percentage points, both are on top of the benchmark return.

Other choices for the benchmark exposures q_i may also come to mind, such as the average factor exposures across pension funds. However, the different choices of the benchmark factor exposures result in a shifted distribution to either the right or left from the one in Table 9 but does not affect the cross-sectional heterogeneity across pension funds.

[Place Table 9 about here]

C. The effect via the choice of asset management firms

We next address the question of whether the differences in implied beliefs are intentional choices by the pension funds. We hypothesize that if beliefs are intentional, then they will show up in the mandates that pension funds give to external asset management firms.

Pension funds do not necessarily manage assets themselves. In fact, most Dutch pension funds delegate the implementation of their investment strategy to for-profit asset management firms through asset management mandates (e.g. Binsbergen et al. 2008; Blake et al. 2013). Although the information on these mandates is scarce, pension funds do report each quarter the name of the asset management firm that executes at least 30 percent of the total AUM on behalf of the pension fund.[18] These firm names are available for the period from 2009 through 2017 and facilitate the analyzation of the effect that the choice of the asset management firm has on factor exposures. Furthermore, to extend the supervision data, we manually check the asset management firm as reported in pension funds' annual reports. Some pension funds report multiple asset management firms (roughly 15 percent of the sample). Because we do not observe in either the supervision data or the annual reports the fraction of assets managed by each of those asset management firms, we are not able to clearly identify the changes due to these firms. Thus, apart from the pension funds that have multiple asset management firms, we can now identify whether pension funds switch from one asset management firm to another and in which quarter.

We have two important reasons to look at changes in asset management firms as opposed to those contracted by the pension fund at a specific point in time. First of all, looking at these changes rules out the possibility that we will find effects simply because the asset management firm correlates with unobservable time-invariant pension fund characteristics. Second, pension funds are likely to hire a new asset management firm if they want to implement a change in their beliefs. In the process of contracting a new asset management firm, pension funds typically do a "search" that is supported by specialised consultants (e.g.

[18] For confidentiality reasons, we cannot disclose the names of the asset management firms.

Del Guercio and Tkac 2002; Goyal and Wahal 2008). Once an asset management firm is selected the mandate is agreed upon according to the preferences of the pension fund.

We focus on asset management firms that were newly hired by at least two pension funds during 2009Q2-2017Q4. A new hire means that we observe a different asset management firm from one quarter to the other. These observations result in a total of 10 asset management firms that gained new business from 59 Dutch pension funds of the 350 pension funds that are in our sample over the period from 2009Q2-2017Q4, which is equivalent to 17 percent of the pension funds. We subsequently run the following regression:[19]

$$r^e_{i,t} \quad = \quad \delta_0' f_t + \delta_1'(f_t \times \text{AM}'_{i,t-1})\iota_{10} + \epsilon_{i,t}, \tag{28}$$

in which $\text{AM}_{i,t-1}$ is a vector of length 10 and equals 1 for each quarter that the corresponding asset management firm is hired by pension fund i after 2009Q1 and zero otherwise; ι_{10} is a vector of ones with length 10.

Table 10 shows the results for this regression and indicates that changing asset management firms has an effect on factor exposures in a substantial amount of cases. For equities, pension funds that contract asset management firms 3, 4, 5, and 6 get a significantly higher exposure to the global market index. Therefore, it is likely that these asset management firms are deliberately hired to implement a more global allocation to equities. Other pension funds hire asset management firm 9 to lower their global equity allocation and to increase their allocation of European equities. Pension funds switching to asset management firm 1 result in higher low beta exposures. Pension funds that hire asset management firm 8 obtain negative carry exposures, while the ones that hire asset management firms 2, 6, and 8 obtain negative low beta exposures. The economic magnitudes of these changes are substantial. For instance, pension funds that hire asset management firm 1 have an exposure of 0.17 to low beta compared to an average exposure across all pension funds of 0.06. For fixed income, we find that hiring asset management firms 5, 6,

[19]For confidentiality reasons, we cannot disclose the names of the asset management firms.

and 7 result in lower exposures to the market index. For high yield, asset management firms 5 and 6 result in a substantially higher credit exposure: 0.26 and 0.37 compared to the average of −0.04. Pension funds that hire asset management firms 3, 7, or 8 have higher value exposures. Asset management firms 3, 6, and 8 result in lower carry exposures.

During the sample period, 59 pension funds switch to one of the ten asset management firms, so we do not have a large power for statistical significance. Despite this, we still find statistical significant, and economically sizeable, effects of asset management firms on some of the factor exposures. We therefore argue that these findings support the idea that factor exposures are at least to a reasonable degree driven by choices about beliefs made by pension funds. Pension funds may change asset management firms for multiple reasons, such as low (excess) returns delivered by the old asset management firm, a change in strategic asset allocation, or a change in beliefs. In most cases pension funds that switch to a new asset management firm will select one that can execute the pension funds' investment policy. And at least a fraction of pension funds will change asset management firms because they have a change in beliefs. This is indeed supported by our analysis. This is furthermore consistent with the findings in Del Guercio and Tkac (2002) who show that quantitative performance variables have a much lower explanatory power in explaining flows for pension fund managers as opposed to mutual fund managers. Importantly, they argue that pension funds regularly change asset management firms because they fail to stay within the guidelines of the investment mandate, regardless of their performance.

[**Place Table 10 about here**]

VII. Effect of the liability discount rate on factor exposures

Pension funds operate in a highly regulated environment; therefore, we find that regulations affect pension fund investment strategies. Halfway through our sample period, pension funds in the Netherlands experienced an important change with the introduction of risk-based regulation in 2007. The main elements of this framework include the marked-to-market valuation of assets and liabilities and a risk-based minimum required funding ratio. For pension funds, one of the key channels through which regulations affect investment strategies is the liability discount rate (Andonov et al. 2017). Before 2007, pension funds in the Netherlands used a fixed rate of 4 percent to discount liabilities. Under such a discount rule, liabilities artificially contain no interest rate risk. The fixed discount rate was replaced by the full term structure of market interest rates in 2007. Consequently, the present value of liabilities fluctuates significantly with changes in the market interest rates. Furthermore, before 2007 there were no risk-based minimum funding requirements. This lack changed in 2007 and since then the risk-based funding requirement has been implemented. This requirement is derived from a well-known value-at-risk (VaR) concept, whereby risk is measured as the mismatch between the assets and liabilities. Pension funds' investment strategies affect the funding requirement. Pension funds that better match assets and liabilities through investing more in long-term bonds, have a lower required funding ratio, and vice versa.

To show the effect of these regulatory changes, we split the sample period in two and identify the factor exposures prior to and after 2007. Table 11 shows the results. We observe a large change in the exposure to the Euro fixed income market index. Prior to 2007, pension funds had an average exposure to the market of 1.02. After 2007 this average exposure increased to 1.23 that reflected that they allocated more to long-term bonds. This finding is consistent with our theoretical framework, because liability hedge demand was nonexistent from a regulatory perspective prior to 2007 but became apparent after 2007. We also observe a decrease in the exposure to the value and carry factors for fixed income. Dutch and German government bonds resemble the risk-free term structure of interest rates better as opposed to Italian and Spanish bonds. Yet, at the same time the former have lower value and carry ranks.[20] These two forces may contribute to a negative exposure to the value

[20] We obtain these ranks from the construction of the European fixed income factors.

and carry factors. For equities, we observe a small shift from global to European stocks. This way pension funds may reduce the exchange rate risk and lower the risk-based funding requirement. Another striking consequence of the change in regulation is the increase to the low beta factor for both equities and fixed income. Because of risk-based regulations, pension funds may aim to decrease the downside risk of their portfolios by investing more in low beta assets. Changes in long-short factor exposures may also result from developments and insights in the literature on factors. We however leave those channels for future research.

[Place Table 11 about here]

VIII. Conclusion

In this study, we provide detailed insight into the investment strategies of defined-benefit pension funds that represent a large fraction of the European market for pension funds' assets. We measure investment strategies through factor exposures within equity and fixed income portfolios. Factor exposures are key to understanding the heterogeneity in the performance and investment strategies of liability-driven investors. We analyse two groups of drivers that influence factor exposures: pension funds' characteristics and institutional factors. These drivers only partially explain investment strategies across pension funds. We attribute the remaining heterogeneity to differences in implied beliefs about factor returns. These differences partially appear through the pension funds' choice of asset management firms to execute their investment policy.

Our results have important policy implications. We suggest that liability-driven investors can use the approach in this study for strategic investment decision-making. Our approach makes a distinction between a liability hedge demand and a speculative demand, that we measure through factor exposures. While the liabilities of a defined benefit pension fund can be measured objectively, a crucial part in the investment strategy is to form beliefs that drive the speculative demand. These are subjective in nature and require careful consideration and decision-making by a pension fund's board of trustees. Further, liability-driven investors should explain this strategy in a clear and transparent way to their stakeholders. This is particularly important because beneficiaries are typically not free to choose their own pension fund as it comes with the job. The exit costs to leave a pension fund if a beneficiary is dissatisfied with the investment strategy are prohibitively high. Employees would need to change jobs to change pension funds and retirees cannot change pension funds whatsoever. Therefore an import fiduciary duty rests on liability-driven investors to invest in the best interest of their beneficiaries.

IX. Appendix

A Model derivation

The mean-variance optimization problem of pension fund i equals:

$$\max_{w_{i,t}} = \max_{w_{i,t}} \mathbb{E}_t \left[\frac{A_{i,t+1} - L_{i,t+1}}{A_{i,t}} \right] - \frac{\gamma_i}{2} \mathrm{Var}_{i,t} \left[\frac{A_{i,t+1} - L_{i,t+1}}{A_{i,t}} \right], \tag{29}$$

subject to

$$w'_{i,t}\iota_M \leq c, \tag{30}$$

$$w_{i,j,t} \geq 0 \ \ \forall j, \tag{31}$$

where the assets equal $A_{i,t+1} = \Big(1 + w'_{i,t}r_{t+1}\Big)A_{i,t}$, the liabilities equal $L_{i,t+1} = \Big(1 + \psi_{i,t}r^b_{t+1}\Big)L_{i,t}$, and the funding ratio equals $F_{i,t} = A_{i,t}/L_{i,t}$.

The Lagrange of this optimization problem equals:

$$\begin{aligned} \mathcal{L}(w_{i,t}, \lambda_{i,t}) &= 1 + w'_{i,t}\mathbb{E}_{i,t}[r_{t+1}] - \Big(1 + \psi_{i,t}\mathbb{E}_{i,t}[r^b_{t+1}]\Big)F^{-1}_{i,t} \\ &- \frac{\gamma_i}{2}\Big(w'_{i,t}\mathrm{Var}_t[r_{t+1}]w_{i,t} + \psi^2_{i,t}\mathrm{Var}_t[r^b_{t+1}]F^{-2}_{i,t} - 2w'_{i,t}\mathrm{Cov}_t[r^b_{t+1}\iota_M, r_{t+1}]\psi_{i,t}\iota_M F^{-1}_{i,t}\Big) \\ &+ \lambda_{i,t}(w'_{i,t}\iota_M - c) + \delta'_{i,t}w_{i,t}. \end{aligned} \tag{32}$$

Taking the derivative with respect to $w_{i,t}$ and $\lambda_{i,t}$ gives:

$$\begin{aligned} \frac{\partial \mathcal{L}(w_{i,t}, \lambda_{i,t})}{\partial w_{i,t}} &= \mathbb{E}_{i,t}[r_{t+1}] - \gamma_i \mathrm{Var}_{i,t}[r_{t+1}]w_{i,t} + \gamma_i \mathrm{Cov}_t[r^b_{t+1}\iota_M, r_{t+1}]\psi_{i,t}\iota_M F^{-1}_{i,t} \\ &+ \lambda_{i,t}\iota_M + \delta_{i,t} = 0, \end{aligned} \tag{33}$$

$$\frac{\partial \mathcal{L}(w_{i,t}, \lambda_{i,t})}{\partial \lambda_{i,t}} = w'_{i,t}\iota_M - c = 0. \tag{34}$$

This results in the optimal weights (7):

$$w_{i,t}^{*} = \underbrace{\frac{\mathbb{E}_{i,t}[r_{t+1}] + \lambda_{i,t}\iota_M + \delta_{i,t}}{\gamma_i \text{Var}_t[r_{t+1}]}}_{\text{speculative portfolio}} + \underbrace{\frac{\text{Cov}_t[r_{t+1}^{b}\iota_M, r_{t+1}]\psi_{i,t}\iota_M}{\text{Var}_t[r_{t+1}]} F_{i,t}^{-1}}_{\text{hedging portfolio}}$$

with $\lambda_{i,t}$:

$$\lambda_{i,t} = \frac{c - \left(\frac{\mathbb{E}_{i,t}[r_{t+1}] + \delta_{i,t}}{\gamma_i \text{Var}_t[r_{t+1}]}\right)' \iota_M - \left(\frac{\text{Cov}_t[r_{t+1}^{b}\iota_M, r_{t+1}]\psi_{i,t}\iota_M}{\text{Var}_t[r_{t+1}]} F_{i,t}^{-1}\right)' \iota_M}{\left(\frac{\iota_M}{\gamma_i \text{Var}_t[r_{t+1}]}\right)' \iota_M}. \tag{34}$$

B *Fixed income factors*

Fixed income returns

The universe of European government bond securities that we analyze consists of Austria, Belgium, Denmark, Finland, France Germany, Italy, Netherlands, Norway, Spain, Sweden, Switzerland, and the UK. We use constant maturity, zero-coupon bond yields from Bloomberg for all countries on a monthly basis from 1994 to 2017. We complement the missing data points prior to 1998 with zero coupon bond yields from Jonathan Wright's webpage for Norway, Sweden, Switzerland, and the UK. We use the Libor counterpart in each country as a proxy for the risk-free rate. The corresponding Bloomberg ticker numbers are listed in Table 13 in the Internet Appendix C. All included countries had investment-grade credit ratings over the entire sample period by Fitch, Moody's, and Standard & Poor's.

We start by deriving the bond returns. Following Koijen et al. (2018), we calculate the price of synthetic $\tau = 1$-month futures on a $T = 10$-year zero-coupon bond each month from the no-arbitrage relation:

$$P_{i,t}^{\tau,syn} = \frac{1}{1 + r_{i,t}^{f}} \frac{1}{(1 + y_{i,t})^{T}}, \tag{35}$$

in which $y_{i,t}$ is the $T = 10$-year zero-coupon bond for country $i = 1, \ldots, J$, and r_{it}^{f} is the corresponding risk-free rate. At expiration, the price of the $\tau = 1$-month futures contract equals:

$$P_{i,t+1}^{\tau-1,syn} = \frac{1}{(1 + y_{i,t+\tau})^{T-\tau}}, \tag{36}$$

where we find $y_{i,t+\tau}$ by linear interpolation. The return on a fully-collateralized, currency-hedged, one-month futures contract equals:

$$r_{i,t}^{syn} = \Big(\frac{(1 + r_{i,t}^f)(1 + y_{i,t})^T}{(1 + y_{i,t+\tau})^{T-\tau}} - 1\Big) \times \Big(1 + \frac{e_{i,t+1} - e_{i,t}}{e_{i,t}}\Big) \tag{37}$$

in which $e_{i,t}$ is the time t exchange rate in euros per unit of foreign currency i. Furthermore, the correction term for the exchange rate equals one for all countries in the euro area (Austria, Belgium, Finland, France, Germany, Italy, Netherlands, and Spain).

Factors

We construct value, momentum, carry, and low beta factors for the fixed income portfolios which are zero-cost long-short portfolios that use all the government bonds specified before. For any security $i = 1, \ldots, J$ at time t with signal S_{it} (value, momentum, carry, or low beta), we weight securities in proportion to their cross-sectional rank based on the signal minus the cross-sectional average rank of that signal:

$$w_{it}^S = c_t(\text{rank}(S_{it}) - \sum_{i=1}^{J} \text{rank}(S_{it})/J), \quad \text{where } S \in (\text{value, momentum, carry, low beta}). \tag{38}$$

The weights across all securities sum to zero and represent a dollar-neutral long-short portfolio. The scalar c_t ensures the overall portfolio is scaled one-dollar long and one-dollar short.

The signals are as follows. As in Asness et al. (2013), we define value as the 5-year change in the 10-year yield (5-year $\triangle y$). For momentum, we use the standard measure, namely, the return over the past 12 months but skip the most recent month. The signal for carry is defined as in Koijen et al. (2018):

$$C_{it} = \frac{(1 + y_{i,t}^{T})^{T}}{(1 + r_{i,t}^{f})(1 + y_{i,t}^{T-\tau})^{T-\tau}}. \tag{39}$$

To construct the low beta factor, we estimate the betas as in Frazzini and Pedersen (2014). The estimated beta for country i is:

$$\hat{\beta}_i = \hat{\rho}\frac{\hat{\sigma}_i}{\hat{\sigma}_m}, \tag{40}$$

in which $\hat{\sigma}_i$ and $\hat{\sigma}_m$ are the estimated volatilities for the bond and the market, and $\hat{\rho}$ is their correlation. We estimate the volatilities and correlations with 1- and 5-year windows respectively. The market is defined as the average return of all bonds in our sample. To reduce the effect of outliers, we follow Frazzini and Pedersen (2014) and shrink the time series estimate of beta to one: $\tilde{\beta}_i = 0.6 \times \hat{\beta}_i + 0.4 \times 1$.

The factor returns for value, momentum, and carry are now constructed as:

$$r_t^S = \sum_{i=1}^{J} w_{it-1}^{S} r_{it}^{syn}, \quad \text{where } S \in (\text{value, momentum, carry}). \tag{41}$$

The factor return for low beta is constructed as:

$$r_t^{\text{S}} = \frac{1}{\beta_{t-1}^{L}}(r_t^L - r_t^f) - \frac{1}{\beta_{t-1}^{H}}(r_t^H - r_t^f), \quad \text{where } S \in (\text{low beta}), \tag{42}$$

and $\beta_{t-1}^{L} = w_{Lt-1}'\hat{\beta}_{t-1}$, $\beta_{t-1}^{H} = w_{Ht-1}'\hat{\beta}_{t-1}$, $r_t^L = w_{Lt-1}' r_t^{syn}$, and $r_t^H = w_{Ht-1}' r_t^{syn}$. The weights w_{Lt-1} (w_{Ht-1}) equal the absolute weights of the long portfolio (short portfolio).

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Table 1. **Total assets under management and number of pension funds**: This table shows the total asssets under management (AUM) in billion euros and the number of pension funds (N). The left hand columns present all pension funds in the Netherlands and the right hand columns all the pension funds that fully report returns and that are used in our analysis. AUM and N are at the end of each year.

	All		**Full reporting**	
year	AUM	N	AUM	N
1999	463.70	663	418.43	315
2000	480.78	676	453.09	408
2001	471.00	656	445.33	429
2002	429.51	658	405.67	447
2003	489.60	642	463.88	439
2004	529.93	605	510.39	450
2005	610.52	575	576.14	365
2006	657.57	524	604.64	390
2007	683.53	442	665.62	403
2008	576.32	413	557.21	376
2009	663.59	376	632.49	336
2010	746.28	350	729.31	328
2011	802.33	329	784.80	298
2012	897.09	260	753.51	287
2013	937.12	258	845.62	245
2014	1,131.74	247	984.73	228
2015	1,146.66	227	1,005.96	195
2016	1,262.54	216	1,122.37	190
2017	1,224.07	200	1,163.47	175

Table 2. **Summary statistics**: Panel A reports the summary statistics for pension fund returns, both equally and value weighted. The mean returns and standard deviations of returns are measured across time and pension funds for 1999Q1-2017Q4. We also report the means and standard deviations for equity and fixed income allocations (percent), duration (years), funding ratio (fraction, as of 2007), required funding ratio (fraction, as of 2009), liability duration (years, as of 2007) and the ratio of actives to total participants (percent) that are computed from the quarterly reports. Panel B gives the summary statistics for the factor returns. For pension fund and factor returns, we report the annualized average return, the annualized standard deviation of the returns, the average skewness of the quarterly returns, and the average kurtosis of the quarterly returns. All returns are in euros.

Panel A: Pension fund returns and characteristics

	mean	stdev	skewness	kurtosis
Equally weighted				
Excess return equity	4.38	21.28	−0.53	3.51
Excess return fixed income	3.89	10.04	0.37	5.18
Value weighted				
Excess return equity	4.80	18.97	−0.45	3.85
Excess return fixed income	3.73	6.91	0.44	5.48
Characteristics				
Equity allocation	31.00	9.14		
Fixed income allocation	58.76	11.78		
Duration fixed income portfolio	8.20	8.71		
Funding ratio	1.16	0.16		
Required funding ratio	1.15	0.13		
Liability duration	18.63	5.53		
Fraction of active participants	64.25	24.89		

Panel B: Factor returns

	mean	stdev	skewness	kurtosis
Euribor 3-month rate	1.94	0.83	0.22	1.76
Excess MSCI World Total Return Index	4.99	17.25	−0.70	3.83
Excess Euro Stoxx 50 Total Return Index	4.07	21.37	−0.32	4.11
Global value stock	4.00	15.81	0.57	11.51
Global momentum stock	5.20	16.88	0.26	6.44
Global carry stock	6.49	6.75	0.17	3.71
Global low beta stock	11.03	11.93	−0.10	6.81
Excess Bloomberg Barclays EuroAgg FI Index	2.55	3.66	−0.39	2.76
Excess Bloomberg Barclays EuroAgg High Yield Index	6.38	14.89	0.42	8.12
Europe value FI	1.17	5.56	−0.27	5.68
Europe momentum FI	1.24	4.54	−0.57	7.89
Europe carry FI	1.84	4.52	0.48	6.46
Europe low beta FI	0.86	4.41	0.18	3.29

Table 3. **Factor exposures**: This table displays the cross-sectional means and standard deviations of the OLS betas from Equation (14), the prior betas from Equation (15), and the posterior betas from Equation (17). M,W indicates the excess global market index for equities, M,EU indicates the excess European market index for the corresponding asset class, HY-EU indicates the excess high yield index for fixed income, VAL, MOM, CARRY, and BAB indicate the value, momentum, carry, and low beta factor for the corresponding asset class.

Panel A: Equity

	OLS		**Prior**		**Posterior**	
	mean	std.dev.	mean	std.dev.	mean	std.dev.
$\hat{\beta}_i^{M,W}$	0.656	0.297	0.649	0.184	0.668	0.179
$\hat{\beta}_i^{M,EU}$	0.270	0.311	0.299	0.160	0.273	0.153
$\hat{\beta}_i^{VAL}$	-0.060	0.230	-0.043	0.085	-0.048	0.066
$\hat{\beta}_i^{MOM}$	-0.056	0.244	-0.041	0.048	-0.044	0.041
$\hat{\beta}_i^{CARRY}$	-0.106	0.549	-0.054	0.148	-0.057	0.126
$\hat{\beta}_i^{BAB}$	0.088	0.240	0.087	0.107	0.075	0.082

Panel B: Fixed income

	OLS		**Prior**		**Posterior**	
	mean	std.dev.	mean	std.dev.	mean	std.dev.
$\hat{\beta}_i^{M,EU}$	1.139	0.564	1.126	0.485	1.107	0.306
$\hat{\beta}_i^{HY,EU}$	0.019	0.111	0.024	0.086	0.023	0.061
$\hat{\beta}_i^{VAL}$	-0.146	0.402	-0.208	0.155	-0.158	0.147
$\hat{\beta}_i^{MOM}$	0.024	0.623	0.071	0.000	0.070	0.007
$\hat{\beta}_i^{CARRY}$	-0.037	0.552	-0.079	0.092	-0.067	0.087
$\hat{\beta}_i^{BAB}$	0.253	0.508	0.271	0.194	0.205	0.176

Table 4. **Heterogeneity of average excess returns**: This table shows the distribution of the average excess return contributions of the market factors, long-short factors, and all factors, to the total equity returns (Panel A), fixed income returns (Panel B), and overall portfolio returns (Panel C). The overall portfolio contribution of the market factors (long-short factors) (all factors) is calculated as the equity weight times the contribution of market factors (long-short factors) (all factors) for equity, plus the fixed income weight times the contribution of the market factor (long-short factors) (all factors) for fixed income. We report the averages within the 0-20th, 20-40th, 40-60th, 60-80th, and 80-100th percentiles. The last column shows the difference between the 100th-80th and the 0-20th percentile. All values are percentage points and annualized.

Panel A: Equity

	0-20th	20-40th	40-60th	60-80th	80-100th	diff
All factors	2.23	3.92	4.66	5.26	6.40	4.17
Global market	3.15	3.49	3.31	3.38	3.32	0.17
EU market	0.96	0.96	1.20	1.17	1.28	0.32
Value	-0.31	-0.23	-0.16	-0.15	-0.10	0.21
Momentum	-0.28	-0.23	-0.22	-0.20	-0.20	0.07
Carry	-1.25	-0.61	-0.33	-0.08	0.44	1.69
Low beta	-0.05	0.55	0.87	1.14	1.66	1.71

Panel B: Fixed income

	0-20th	20-40th	40-60th	60-80th	80-100th	diff
All factors	1.91	2.61	2.93	3.29	3.95	2.04
Market	1.99	2.53	2.76	3.10	3.82	1.83
High yield	0.07	0.11	0.19	0.23	0.14	0.07
Value	-0.18	-0.12	-0.17	-0.22	-0.24	-0.06
Momentum	0.09	0.09	0.09	0.09	0.09	0.00
Carry	-0.17	-0.11	-0.12	-0.12	-0.09	0.08
Low beta	0.12	0.11	0.18	0.21	0.24	0.13

Panel C: Overall portfolio

	0-20th	20-40th	40-60th	60-80th	80-100th	diff
All factors	2.21	3.02	3.51	3.93	4.56	2.35
Market factors	2.74	3.24	3.46	3.78	4.04	1.31
Long-short factors	-0.53	-0.21	0.05	0.15	0.51	1.04

Table 5. **Variance decomposition**: This table shows how much of the variance in estimated average excess returns $\tilde{\mu}$ is explained by the alpha and the factor exposures for equities and fixed income presented in Equation (21). We calculate the average return per asset class of each pension fund using $\tilde{\mu}_i = \tilde{\alpha}_i + \tilde{\beta}_i' \lambda$ in which λ is the average factor return. All values are percentages.

Variance contribution			
Equity		Fixed income	
α	−7.08	α	13.28
Global market	14.05	Market	71.32
EU market	5.41	High yield	2.79
Value	3.67	Value	1.53
Momentum	2.58	Momentum	−0.22
Carry	40.15	Carry	6.48
Low beta	41.22	Low beta	4.83

Table 6. **Effect of pension fund's characteristics on factor exposures**: This table shows the coefficient estimates of Equation (22): We regress the pension funds' excess returns on the factor returns and the factor returns interacted with the funding ratio, the risk aversion coefficient that we represent with the inverse of the required funding ratio, and the liability duration during the period from 2009Q1-2017Q4. We control in both specifications for the model parameters included in Table 7. Standard errors are in parentheses and clustered at the pension fund level; $^{*}p < 0.10$, $^{**}p < 0.05$, and $^{***}p < 0.01$.

Panel A: Equity

	average	funding ratio	risk aversion	liability duration
$\beta^{M,W}$	0.646***	-0.0012	-0.302*	0.0042***
	[0.0144]	[0.0538]	[0.1757]	[0.0013]
$\beta^{M,EU}$	0.289***	0.0445	0.0052	-0.0032**
	[0.0209]	[0.0459]	[0.1806]	[0.0013]
β^{VAL}	0.041	-0.107	0.2520	0.0017
	[0.0299]	[0.0977]	[0.3615]	[0.0025]
β^{MOM}	-0.0668***	-0.0363	0.1300	-0.0012
	[0.0231]	[0.0645]	[0.2218]	[0.0015]
β^{CARRY}	0.0193	0.0836	-0.3960	0.001
	[0.0219]	[0.1253]	[0.3019]	[0.0020]
β^{BAB}	0.132***	0.0451	0.0068	-0.0041**
	[0.0203]	[0.0603]	[0.2308]	[0.0018]
obs.	8,774	adj. R-sq.	0.863	

Panel B: Fixed income

	average	funding ratio	risk aversion	liability duration
$\beta^{M,EU}$	2.193***	-1.123***	9.755***	0.0736***
	[0.1579]	[0.2414]	[1.4087]	[0.0161]
$\beta^{HY,EU}$	-0.0272*	0.107***	-0.749***	-0.0058***
	[0.0157]	[0.0345]	[0.1570]	[0.0013]
β^{VAL}	-0.121***	-0.0036	-0.965*	-0.0084*
	[0.0464]	[0.0919]	[0.5134]	[0.0048]
β^{MOM}	0.0636*	-0.0685	1.016***	-0.0002
	[0.0338]	[0.0617]	[0.3225]	[0.0031]
β^{CARRY}	-0.667***	0.4270**	-3.732***	-0.0255**
	[0.1024]	[0.1767]	[0.9643]	[0.0108]
β^{BAB}	-0.170**	0.1680	-1.699**	-0.0129
	[0.0763]	[0.1306]	[0.7453]	[0.0084]
obs.	8,856	adj. R-sq.	0.574	

Table 7. **Effect of institutional factors on factor exposures**: We regress the pension funds' excess returns on the factor returns and the factor returns interacted with the log AUM (size) and the pension fund type (base group: industry pension funds, other groups: corporate and professional group pension funds) during the period from 2009Q1-2017Q4. We control in both specifications for the model parameters included in Table 6. Panel A shows the results for equities and Panel B for fixed income. Standard errors are in parentheses and clustered at the pension fund level; $^{*}p < 0.10$, $^{**}p < 0.05$, and $^{***}p < 0.01$.

Panel A: Equity

	average	size	corporate	professional
$\beta^{M,W}$	0.646***	0.0558***	0.0590***	0.0285
	[0.0144]	[0.0085]	[0.0156]	[0.0236]
$\beta^{M,EU}$	0.289***	-0.0506***	-0.0301	-0.0161
	[0.0209]	[0.0084]	[0.0210]	[0.0261]
β^{VAL}	0.041	-0.0127	-0.0098	0.0271
	[0.0299]	[0.0154]	[0.0310]	[0.0433]
β^{MOM}	-0.0668***	-0.0084	0.0199	0.0283
	[0.0231]	[0.0111]	[0.0230]	[0.0361]
β^{CARRY}	0.0193	0.0004	-0.0196	-0.0626*
	[0.0219]	[0.0130]	[0.0229]	[0.0361]
β^{BAB}	0.132***	-0.0057	-0.0326*	0.0052
	[0.0203]	[0.0110]	[0.0177]	[0.0324]
obs.	8,774	adj. R-sq.	0.863	

Panel B: Fixed income

	average	size	corporate	professional
$\beta^{M,EU}$	2.193***	0.1170	-0.0422	-0.3200
	[0.1579]	[0.0960]	[0.1828]	[0.2920]
$\beta^{HY,EU}$	-0.0272*	0.0125	-0.0067	0.001
	[0.0157]	[0.0099]	[0.0176]	[0.0317]
β^{VAL}	-0.121***	-0.0366	-0.0644	0.0914
	[0.0464]	[0.0295]	[0.0543]	[0.1125]
β^{MOM}	0.0636*	-0.0162	-0.0675*	-0.0019
	[0.0338]	[0.0194]	[0.0384]	[0.0724]
β^{CARRY}	-0.667***	-0.0566	0.1810	0.1180
	[0.1024]	[0.0635]	[0.1204]	[0.1955]
β^{BAB}	-0.170**	0.0138	0.1350	0.1420
	[0.0763]	[0.0469]	[0.0894]	[0.1629]
obs.	8,856	adj. R-sq.	0.574	

Table 8. **Remaining heterogeneity of average excess returns**: This table shows the distribution of the average excess return contributions of market factors, long-short factors, and all factors to the overall portfolio returns for unadjusted returns (Panel A), returns corrected for the pension fund characteristics (Panel B), and corrected for both the pension fund characteristics and the institutional factors (Panel C). Panel D uses the same specification as Panel C but for pension funds that are at least 24 quarters in the sample. The overall portfolio contribution of the market factors (long-short factors) (all factors) is calculated as the equity weight times the contribution of market factors (long-short factors) (all factors) for equity, plus the fixed income weight times the contribution of the market factor (long-short factors) (all factors) for fixed income. We report the averages within the 0-20th, 20-40th, 40-60th, 60-80th, and 80-100th percentiles. The last column shows the difference between the 80th-100th and the 0-20th percentile. All values are percentage points and annualized.

Panel A: Unadjusted returns

	0-20th	20-40th	40-60th	60-80th	80-100th	diff.
All factors	2.21	3.02	3.51	3.93	4.56	2.35
Market factors	2.74	3.24	3.46	3.78	4.04	1.30
Long-short factors	-0.53	-0.21	0.05	0.15	0.51	1.04

Panel B: Returns corrected for pension fund characteristics

	0-20th	20-40th	40-60th	60-80th	80-100th	diff.
All factors	2.97	3.36	3.65	4.05	4.47	1.50
Market factors	3.22	3.57	3.54	3.82	3.91	0.69
Long-short factors	-0.25	-0.20	0.10	0.23	0.56	0.81

Panel C: Returns corrected for pension fund characteristics and institutional factors

	0-20th	20-40th	40-60th	60-80th	80-100th	diff.
All factors	3.15	3.58	3.86	4.30	4.65	1.50
Market factors	3.39	3.78	3.73	4.05	4.07	0.68
Long-short factors	-0.24	-0.21	0.13	0.25	0.58	0.82

Panel D: Subsample of pension funds

	0-20th	20-40th	40-60th	60-80th	80-100th	diff.
All factors	2.95	3.42	3.55	3.85	4.11	1.16
Market factors	3.21	3.48	3.60	3.81	3.94	0.73
Long-short factors	-0.26	-0.07	-0.04	0.04	0.17	0.43

Table 9. **Implied beliefs on expected factor returns**: Panel A gives the statistics of the implied beliefs on the expected factor returns for equities, and Panel B shows the results for fixed income. Column 1 shows the historical mean of the factor returns over our sample period, and columns 2-6 show the implied beliefs on top of the benchmark return. The results are derived from Equation (27). Panel A shows the results for equities and Panel B for fixed income. We report the 10th, 25th, 50th, 75th, and 90th percentiles. All values are percentage points and annualized.

Panel A: Equity

	mean	**10th**	**25th**	**50th**	**75th**	**90th**
Benchmark return	4.99					
Global market index	4.99	-1.53	-0.79	-0.12	0.12	0.71
European market index	4.07	-0.18	0.00	1.10	1.86	2.70
Value	4.00	-0.34	0.00	0.41	0.85	1.30
Momentum	5.20	-1.01	-0.70	-0.40	0.00	0.06
Carry	6.49	-0.55	-0.40	-0.21	0.00	0.00
Low beta	11.03	-0.15	0.00	0.39	0.75	1.11

Panel B: Fixed income

	mean	**10th**	**25th**	**50th**	**75th**	**90th**
Benchmark return	2.55					
Global market index	2.55	-0.33	-0.19	-0.03	0.02	0.17
High yield	6.38	-1.18	-0.78	-0.19	0.08	0.49
Value	1.17	-0.71	-0.59	-0.46	-0.16	0.00
Momentum	1.24	0.00	0.11	0.28	0.39	0.47
Carry	1.84	-0.41	-0.34	-0.27	-0.14	0.00
Low beta	0.86	0.00	0.11	0.45	0.66	0.81

Table 10. **Effect of asset management firm changes on factor exposures**: This table shows the coefficient estimates of Equation (28): We regress the pension funds' excess returns on the factor returns and the factor returns interacted with the changes in asset management firms (AM1-AM10) during the period from 2009Q2-2017Q4. Panel A shows the results for equities and Panel B for fixed income. Standard errors are in parentheses and clustered at the pension fund level; $^{*}p < 0.10$, $^{**}p < 0.05$, and $^{***}p < 0.01$.

Panel A: Equity

	average	AM1	AM2	AM3	AM4	AM5
$\beta^{M,W}$	0.711***	-0.055	-0.168	0.0890**	0.122**	0.101**
	[0.0063]	[0.0492]	[0.1094]	[0.0352]	[0.0546]	[0.0478]
$\beta^{M,EU}$	0.242***	-0.0075	0.330***	-0.0367	-0.169***	-0.126***
	[0.0057]	[0.0377]	[0.1176]	[0.0321]	[0.0458]	[0.0436]
β^{VAL}	0.0311**	-0.0474	-0.260*	-0.0095	-0.218**	0.0871
	[0.0123]	[0.0728]	[0.1547]	[0.0515]	[0.0952]	[0.0991]
β^{MOM}	-0.0552***	-0.0112	0.139	0.0168	-0.222***	0.0047
	[0.0076]	[0.0506]	[0.1320]	[0.0419]	[0.0708]	[0.0690]
β^{CARRY}	0.0271***	-0.0298	0.218	-0.0388	0.0092	-0.144
	[0.0090]	[0.0689]	[0.1615]	[0.0352]	[0.0803]	[0.1003]
β^{BAB}	0.0551***	0.110**	-0.432***	-0.0336	0.0029	0.0687
	[0.0144]	[0.0550]	[0.1655]	[0.0330]	[0.0530]	[0.0965]
		AM6	AM7	AM8	AM9	AM10
$\beta^{M,W}$		0.132***	-0.0465	0.0585	-0.201***	-0.0727
		[0.0427]	[0.0862]	[0.0415]	[0.0448]	[0.0772]
$\beta^{M,EU}$		-0.141***	-0.0734	-0.0098	0.196***	0.0901
		[0.0351]	[0.0617]	[0.0339]	[0.0401]	[0.0688]
β^{VAL}		-0.0247	-0.175	-0.0069	0.00053	-0.1120
		[0.0659]	[0.1138]	[0.0623]	[0.0953]	[0.0995]
β^{MOM}		-0.0801*	-0.101	-0.00486	-0.0185	-0.001
		[0.0418]	[0.0953]	[0.0420]	[0.0626]	[0.0823]
β^{CARRY}		-0.0263	0.0037	-0.0948**	0.0208	0.126
		[0.0544]	[0.1218]	[0.0460]	[0.0698]	[0.1010]
β^{BAB}		-0.0917**	0.137	-0.109**	0.0607	-0.0452
		[0.0383]	[0.1159]	[0.0510]	[0.0711]	[0.1030]
obs.	9,319	adj. R-sq.	0.867			

Panel B: Fixed income

	average	AM1	AM2	AM3	AM4	AM5
$\beta^{M,EU}$	2.183***	-0.21	-0.787	0.702	0.778	-0.795***
	[0.0550]	[0.3366]	[2.2588]	[0.5028]	[0.7524]	[0.1811]
$\beta^{HY,EU}$	-0.0444***	-0.0351	0.506	-0.124	-0.111	0.306***
	[0.0064]	[0.0813]	[0.7004]	[0.1872]	[0.2772]	[0.0778]
β^{VAL}	-0.175***	0.0537	-0.764	0.273**	0.39	0.104
	[0.0197]	[0.1203]	[1.1188]	[0.1146]	[0.3567]	[0.0893]
β^{MOM}	0.0285**	-0.0906	-0.081	0.250*	-0.0806	0.118
	[0.0120]	[0.0722]	[0.3436]	[0.1394]	[0.1747]	[0.1375]
β^{CARRY}	-0.486***	0.125	0.828	-0.948***	-0.236	-0.126
	[0.0374]	[0.1967]	[1.2438]	[0.2721]	[0.4979]	[0.1491]
β^{BAB}	-0.0585**	0.303	0.761	-0.378*	0.644	0.117
	[0.0278]	[0.2233]	[0.8373]	[0.2253]	[0.4971]	[0.1055]
		AM6	AM7	AM8	AM9	AM10
$\beta^{M,EU}$		-0.816**	-1.055***	0.983	1.102	1.084
		[0.3786]	[0.3360]	[0.7955]	[0.7147]	[0.9558]
$\beta^{HY,EU}$		0.416***	0.12	-0.236	-0.197	-0.144
		[0.1514]	[0.0967]	[0.2169]	[0.2181]	[0.2972]
β^{VAL}		0.125	0.200***	0.486**	0.203	0.00876
		[0.0970]	[0.0727]	[0.2178]	[0.2409]	[0.3613]
β^{MOM}		0.0168	-0.0704	0.0525	0.195	0.112
		[0.0838]	[0.0795]	[0.1485]	[0.1746]	[0.2104]
β^{CARRY}		-0.356*	0.229	-0.870*	-0.695	-0.263
		[0.1984]	[0.1834]	[0.4476]	[0.4285]	[0.5508]
β^{BAB}		-0.32	-0.182	-0.453	-0.136	-0.268
		[0.1958]	[0.1712]	[0.3198]	[0.3482]	[0.4591]
obs.	9,435	adj. R-sq.	0.534			

Table 11. **Factor exposures before and after a change in regulations**: This table displays the cross-sectional means and standard deviations of the posterior betas from Equation (17) estimated for the period prior to 2007 and the period thereafter. The last column shows the difference between the average posterior betas in the two subsamples and the significance of the difference is based on a t-test; $^{*}p < 0.10$, $^{**}p < 0.05$, and $^{***}p < 0.01$. Panel A shows the results for equities and Panel B for fixed income. M,W indicates the excess global market index for equities, M,EU indicates the excess European market index for the corresponding asset class, HY-EU indicates the excess high yield index for fixed income, VAL, MOM, CARRY, and BAB indicate the value, momentum, carry, and low beta factor for the corresponding asset class.

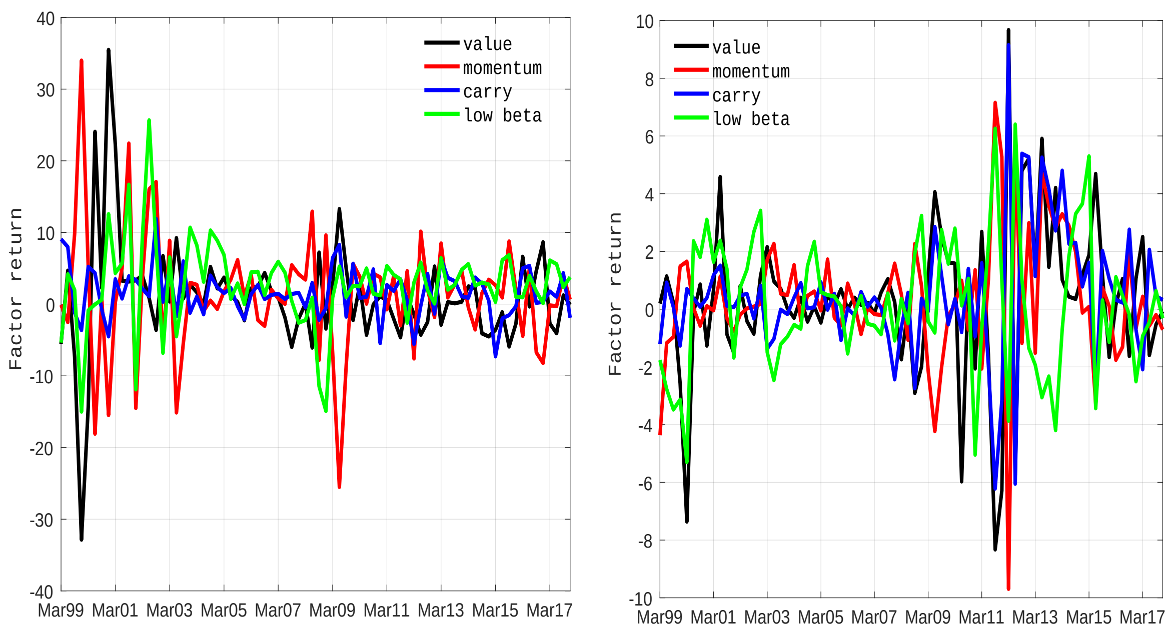
Panel A: Equity

	full		*prior 2007*		*after 2007*		
	mean	std.dev.	mean	std.dev.	mean	std.dev.	diff. *after* - *prior*
$\hat{\beta}_i^{M,W}$	0.668	0.179	0.676	0.208	0.645	0.207	-0.031
$\hat{\beta}_i^{M,EU}$	0.273	0.153	0.228	0.165	0.296	0.170	0.068^{***}
$\hat{\beta}_i^{VAL}$	-0.048	0.066	-0.064	0.071	-0.036	0.093	0.029^{***}
$\hat{\beta}_i^{MOM}$	-0.044	0.041	-0.057	0.060	-0.041	0.056	0.016^{***}
$\hat{\beta}_i^{CARRY}$	-0.057	0.126	-0.193	0.400	0.010	0.073	0.203^{***}
$\hat{\beta}_i^{BAB}$	0.075	0.082	0.031	0.071	0.132	0.113	0.101^{***}

Panel B: Fixed income

	full		*prior 2007*		*after 2007*		
	mean	std.dev.	mean	std.dev.	mean	std.dev.	diff. *after* - *prior*
$\hat{\beta}_i^{M,EU}$	1.107	0.306	1.021	0.115	1.232	0.377	0.211^{***}
$\hat{\beta}_i^{HY,EU}$	0.023	0.061	0.017	0.008	0.023	0.096	0.006
$\hat{\beta}_i^{VAL}$	-0.158	0.147	-0.013	0.008	-0.242	0.181	-0.229^{***}
$\hat{\beta}_i^{MOM}$	0.070	0.007	-0.029	0.004	0.070	0.004	0.099^{***}
$\hat{\beta}_i^{CARRY}$	-0.067	0.087	0.033	0.024	-0.060	0.128	-0.092^{***}
$\hat{\beta}_i^{BAB}$	0.205	0.176	0.033	0.034	0.299	0.213	0.266^{***}

Figure 1. **Long-short factor returns**: This figure shows the global (equity) and European (fixed income) quarterly long-short factor returns over our sample period, 1999Q1-2017Q4.



Equities factors **Fixed income factors**

X. Internet Appendix

A Total AUM by pension funds in the euro area

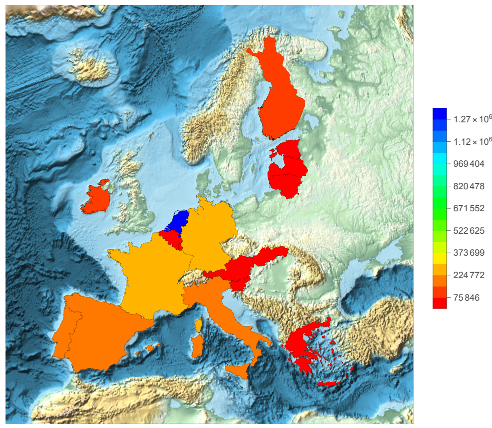


Figure 2. Total assets in million EUR in funded and private pension plans (OECD 2019).

B Random-Coefficients Model

We make the following assumptions when estimating the regression in Equation (15):

1. $\alpha_i = \alpha + u_i$ and $u_i \sim N(0, \sigma_\alpha^2)$

2. $\beta_i = \beta + v_i$ and $v_i \sim N(0, G)$, where

$$G = \mathbb{E}(v_k v_j') = \begin{cases} \sigma^2_{\beta^k} & \text{for} \quad j = k \\ \sigma_{\beta^k \beta^j} & \text{for} \quad j \neq k \end{cases} \tag{43}$$

3. $\{\epsilon_{it}\}_{i,t=1}^{N,T} \perp\!\!\!\perp \{u_i\}_{i=1}^{N} \perp\!\!\!\perp \{v_i\}_{i=1}^{N}$.

In almost all cases, we assume independence across the random effects of the factor exposures, that is, $\sigma_{\beta^k \beta^j} = 0$, except for the two market factors for equities. Because the Euro Stoxx 50 index is a subset of the MSCI World Index, a higher exposure to the Euro Stoxx 50 Index directly indicates a lower exposure to the MSCI World Index, and vice versa.[21]

[21] We perform a simulation test to ensure the high correlation between the MSCI World Index and the Euro Stoxx 50 Index does not cause multicollinearity problems. We simulate returns consisting of a mix between the MSCI World Index, the Euro Stoxx 50 Index, and an error term. We then regress the simulated returns on the MSCI World Index and the Euro Stoxx 50 index. We find the exact coefficients with high precision (i.e., low standard errors) that we imposed for the simulated returns.

The random-coefficients model is estimated using maximum likelihood. We show the derivation here for equities. The procedure works in the same way for fixed income, except that we allow for no correlations between the random coefficients.

To derive the likelihood, we start with writing Equation (15) in vector notation:[22]

$$r_i^e = \alpha \iota_T + \beta' f + v_i' f + u_i + \epsilon_i, \tag{44}$$

in which r_i^e is the $T \times 1$ vector of excess returns for fund i, f is the $T \times k$ matrix of factor returns for the fixed effects $\beta = \begin{bmatrix} \beta^1 \\ .. \\ \beta^K \end{bmatrix}$ and the random effect $v_i = \begin{bmatrix} v_i^1 \\ .. \\ v_i^K \end{bmatrix}$, and u_i is the random intercept.

The $T \times 1$ vector of errors ϵ_i is assumed to be multivariate normal with a mean zero and variance matrix $\sigma_\epsilon^2 \mathbf{I}_T$. We have:

$$\text{Var} \begin{bmatrix} \alpha_i \\ v_i^1 \\ .. \\ v_i^K \\ \epsilon_i \end{bmatrix} = \begin{bmatrix} \sigma_\alpha^2 \iota_T \ \iota_T' & 0 & 0 & 0 & 0 \\ 0 & \sigma_{\beta^1}^2 \iota_T \iota_T' & \sigma_{\beta^1 \beta^2} \iota_T \iota_T' & 0 & 0 \\ 0 & \sigma_{\beta^2 \beta^1} \iota_T \iota_T' & \ddots & 0 & 0 \\ 0 & 0 & 0 & \sigma_{\beta^K}^2 \iota_T \iota_T' & 0 \\ 0 & 0 & 0 & 0 & \sigma_\epsilon^2 \mathbf{I}_T \end{bmatrix}. \tag{45}$$

The error term: $v_i^1 f^1 + ... + v_i^K f^K + u_i + \epsilon_i$ has a $T \times T$ variance-covariance matrix

$$V = \text{Var}[r_i^e | f] = \sigma_\alpha^2 \iota_T \ \iota_T' + \sigma_{\beta^1}^2 f^1 f^{1'} + 2\sigma_{\beta^1 \beta^2} f^1 f^{2'} + \sigma_{\beta^2}^2 f^2 f^{2'} + ... + \sigma_{\beta^K}^2 f^K f^{K'} + \sigma_\epsilon^2 \mathbf{I}_T. \tag{46}$$

The log-likelihood for fund i can now be written as:

$$L_i(\alpha, \beta, \sigma_\alpha^2, \sigma_{\beta^1}^2, ..., \sigma_{\beta^K}^2, \sigma_\epsilon^2 | r_i^e) = -\frac{1}{2} \{ T \log(2\pi) + \log |V| + (r_i^e - \alpha \iota_T - \beta' f)' V^{-1} (r_i^e - \alpha \iota_T - \beta' f) \}. \tag{47}$$

[22] Here we assume all pension funds have the same T. For pension funds with different T, the T should be replaced by T_i.

Then, the total log-likelihood equals:

$$L(\alpha,\beta,\sigma_\alpha^2,\sigma_{\beta 1}^2,...,\sigma_{\beta K}^2,\sigma_\epsilon^2|r^e) = -\frac{1}{2}\{NT\log(2\pi)+N\log|V|+\sum_{i=1}^{N}(r_i^e-\alpha\iota_T-\beta' f)'V^{-1}(r_i^e-\alpha\iota_T-\beta' f)\}. \tag{48}$$

We now turn to a detailed description of the estimation results described in Table 16. We begin by analyzing the results for equities. The exposure to the global market factor equals 0.65, and the exposure to the European factor equals 0.30. Both are statistically significant. The positive and significant exposure to the excess European market return displays the existence of a currency bias; that is, Dutch pension funds on average tend to invest more in Europe relative to the global market portfolio. Additionally, sizable cross-sectional variation exists in pension funds' market betas. The exposure to the global market factor varies between 0.28 and 1.02, and the exposure to the European market factor varies between −0.02 and 0.62. Pension funds on average have significantly negative exposures to value (−0.04), momentum (−0.04), and carry (−0.05). Significant cross-sectional variation exists in all three factor exposures. The highest cross-sectional standard deviation equals 0.15 for the carry factor that indicates the range of factor exposures is between −0.35 and 0.24. The exposure to value varies between −0.21 and 0.13, and between −0.14 and 0.05 for momentum. Pension funds on average have a significantly positive exposure to the low beta factor that is equal to 0.09. Again, we find significant and substantial cross-sectional variation in the low beta exposure that ranges from −0.13 to 0.30.

In case of fixed income, pension funds have an average (significant) exposure to the investment-grade market factor that is equal to 1.13. The cross-sectional variation ranges from 0.16 to 2.10. For the fixed income factors we find that pension funds, on average, have a negative exposure to value (−0.21) and carry (−0.08), a positive exposure to momentum (0.07), and a strong positive exposure to low beta (0.27). The exposure to value varies between −0.52 and 0.10, between −0.27 and 0.11 for carry, and between −0.12 and 0.66 for low beta. The cross-sectional heterogeneity is significant at the 1 percent level for the market factors, value, and low beta, and at the 5 percent level for carry. We are unable to statistically detect significant cross-sectional variation in momentum exposures based on the random-coefficients model.

For equities, we also find cross-sectional variation in alphas, or the part of the return that is not explained by the factors. The standard deviation equals 0.0028, and the alphas vary between −0.0064 and 0.0048 on a quarterly basis. For fixed income we do not observe statistically significant variation in the alphas. This finding indicates that pension funds are unable to outperform each other consistently. However, even if pension funds slightly vary in their alphas, our sample might not have enough observations to say something statistically meaningful about the alphas. This finding is expected, because first moments can be estimated less accurately than second moments (Merton 1980).

C Additional tables

Table 12. **Glossary of symbols**: This table summarizes the main symbols in this study.

Symbol	*Description*
A	Asset value
AM	Vector of asset management firms
AUM	Total asset under management for the corresponding asset class
B	Pension benefits
D	Liability duration
F	Funding ratio
K	Total number of factors
L	Present discounted value of future pension benefits
M	Total number of assets
N	Total number of pension funds
RFR	Required funding ratio
Type	Pension fund type
f_t^a	Vector of factor returns for asset class a
r	Vector of asset returns
r^a	Pension fund return for asset class a
r^b	Return on the risk-free bonds traded in the market
r^e	Pension fund excess return (relative to short-term risk-free rate)
r^f	Short-term risk-free rate
r^h	Regulatory discount rate for time-to-maturity h
r^L	Liability return
w	Vector of portfolio weights
q	Benchmark factor exposures
$se(\beta_i^k)$	Standard error of the time-series OLS factor exposures for factor k
v	Vector of random-effect coefficients
β^a	Vector of factor exposures for asset class a
$\hat{\beta}^k$	Fixed-effect estimator for factor k (prior mean)
$\tilde{\beta}^k$	Posterior factor exposure for factor k
$\hat{\beta}_i^k$	Time-series OLS factor exposures for factor k
$\tilde{\beta}_{adj}^k$	Posterior factor exposures adjusted for pension fund characteristics
γ	Risk aversion coefficient
δ	Kuhn-Tucker multipliers for the short-sale constraints
ι	Vector of ones
λ	Lagrange multiplier for the borrowing constraint
λ^k	Historical average return for factor k
μ	Expected (excess) returns
Σ	Variance-covariance matrix of returns
$\hat{\sigma}_{\beta^k}^2$	Variance estimator of the random effects for factor k (prior variance)
$\tilde{\sigma}_{\beta^k}^2$	Posterior variance for factor k
ψ	Duration of the liabilities over the duration of the risk-free bonds

Table 13. **Bloomberg ticker list**: The Bloomberg ticker numbers used to construct the European fixed income factors described in Appendix B. The x in each ticker number should be replaced by the corresponding maturity: x=10 years, x=09 years, and x=03 months; and y by the corresponding unit of time: y=y for years and y=m for months.

Country	Ticker
Austria	F908xy Index
Belgium	F900xy Index
Denmark	F267xy Index
Finland	F919xy Index
France	F915xy Index
Germany	F910xy Index
Italy	F905xy Index
Netherlands	F920xy Index
Norway	F266xy Index
Spain	F902xy Index
Sweden	F259xy Index
Switzerland	F256xy Index
U.K.	F110xy Index

Table 14. **Correlation table of factor returns**: This table provides the correlation matrix of the factor returns. MSCI-W is the excess MSCI World Total Return Index, EU-50 is the excess Euro Stoxx 50 Total Return Index, VAL-S is the global value factor for stocks, MOM-S is the global momentum factor for stocks, Carry-S is the global carry factor for stocks, and BAB-S is the global low beta factor for stocks. FI-EU is the excess Bloomberg Barclays Euro Aggregate Total Return Bond Index, HY-EU is the Bloomberg Barclays Euro High Yield Index, VAL-FI is the European value factor for fixed income, MOM-FI is the European momentum factor for fixed income, CARRY-FI is the European carry factor for fixed income, and BAB-FI is the European low beta factor for fixed income. All returns are converted into euro returns.

Correlation matrix

	MSCI-W	EU-50	VAL-S	MOM-S	CARRY-S	BAB-S	FI-EU	HY-EU	VAL-FI	MOM-FI	CARRY-FI	BAB-FI
MSCI-W	1											
EU-50	0.87	1										
VAL-S	−0.22	−0.11	1									
MOM-S	−0.18	−0.24	−0.68	1								
CARRY-S	−0.15	−0.26	0.03	−0.01	1							
BAB-S	−0.32	−0.30	0.25	0.13	0.14	1						
FI-EU	−0.15	−0.13	0.11	−0.07	0.08	0.04	1					
HY-EU	0.64	0.63	0.04	−0.41	0.15	−0.10	0.09	1				
VAL-FI	0.18	0.26	0.17	−0.19	−0.03	0.13	0.06	0.37	1			
MOM-FI	−0.12	−0.11	−0.08	0.20	−0.05	−0.06	0.05	−0.34	−0.51	1		
CARRY-FI	0.16	0.27	0.12	−0.17	−0.03	0.10	0.33	0.30	0.66	−0.34	1	
BAB-FI	−0.29	−0.34	0.21	−0.01	0.00	0.10	0.37	−0.25	−0.29	0.31	−0.29	1

Table 15. **OLS factor exposures**: This table displays the cross-sectional mean and standard deviation of the estimated betas from the time-series regression presented in Equation (14). The cross-sectional mean and standard deviation of the R-squared from the time-series regressions are also provided. 10%-level and 5%-level sign. indicate the number of pension funds for which the corresponding factor is statistically different from zero at the 5% and 10% significance level, respectively, by using the Newey-West adjusted standard errors. M,W indicates the excess global market index for equities, M,EU indicates the excess European market index for the corresponding asset class, HY-EU indicates the excess high yield index for fixed income, VAL, MOM, CARRY, and BAB indicate the value, momentum, carry, and low beta factor for the corresponding asset class.

Equity returns

	mean	std.dev.	5%-level sign.	10%-level sign.
$\hat{\beta}_i^{M,W}$	0.656	0.297	531	537
$\hat{\beta}_i^{M,EU}$	0.270	0.311	429	455
$\hat{\beta}_i^{VAL}$	−0.060	0.230	131	182
$\hat{\beta}_i^{MOM}$	−0.056	0.244	143	192
$\hat{\beta}_i^{CARRY}$	−0.106	0.549	139	196
$\hat{\beta}_i^{BAB}$	0.088	0.240	221	269
R^2	0.928	0.092		

Fixed income returns

	mean	std.dev.	5%-level sign.	10%-level sign.
$\hat{\beta}_i^{M,EU}$	1.139	0.564	553	559
$\hat{\beta}_i^{HY,EU}$	0.019	0.111	206	256
$\hat{\beta}_i^{VAL}$	−0.146	0.402	218	274
$\hat{\beta}_i^{MOM}$	0.024	0.623	93	119
$\hat{\beta}_i^{CARRY}$	−0.037	0.552	101	132
$\hat{\beta}_i^{BAB}$	0.253	0.508	249	310
R^2	0.760	0.185		

Table 16. **Prior factor exposures**: This table shows the coefficient estimates and corresponding standard errors for the random-coefficients model in Equation (15) that is used as a prior to compute the posterior betas. The estimates $\hat{\alpha}$ and $\hat{\beta}^k$ indicate the fixed effects, and $\hat{\sigma}^2_\alpha$, and $\hat{\sigma}^2_k$ indicate the random effects of the random-coefficients model. M,W indicates the excess global market index for equities, M,EU indicates the excess European market index for the corresponding asset class, HY-EU indicates the excess high yield index for fixed income, VAL, MOM, CARRY, and BAB indicate the value, momentum, carry, and low beta factor for the corresponding asset class. Standard errors are clustered at the pension fund level; $^{*}p < 0.10$, $^{**}p < 0.05$, and $^{***}p < 0.01$. The significance for each random coefficient is determined by performing a LR-test. The LR-test compares the full random-coefficients model with a random-coefficients model that assumes the factor exposure of interest to be fixed.

Equity returns			Fixed income returns		
	Coefficient	std. error		Coefficient	std. error
$\hat{\alpha}$	-0.001^{**}	0.0003	$\hat{\alpha}$	0.001^{***}	0.0002
$\hat{\beta}^{M,W}$	0.649^{***}	0.0096	$\hat{\beta}^{M,EU}$	1.126^{***}	0.0226
$\hat{\beta}^{M,EU}$	0.299^{***}	0.0083	$\hat{\beta}^{HY,EU}$	0.024^{***}	0.0046
$\hat{\beta}^{VAL}$	-0.043^{***}	0.0051	$\hat{\beta}^{VAL}$	-0.208^{***}	0.0093
$\hat{\beta}^{MOM}$	-0.041^{***}	0.0042	$\hat{\beta}^{MOM}$	0.071^{***}	0.0081
$\hat{\beta}^{CARRY}$	-0.054^{***}	0.0102	$\hat{\beta}^{CARRY}$	-0.079^{***}	0.0122
$\hat{\beta}^{BAB}$	0.087^{***}	0.0063	$\hat{\beta}^{BAB}$	0.271^{***}	0.0117
$\hat{\sigma}^2_{\alpha}$	0.00001^{*}	0.0000	$\hat{\sigma}^2_{\alpha}$	0.0000005	0.0000
$\hat{\sigma}^2_{M,W}$	0.0338^{***}	0.0049	$\hat{\sigma}^2_{M,EU}$	0.235^{***}	0.0904
$\hat{\sigma}^2_{M,EU}$	0.0256^{***}	0.0043	$\hat{\sigma}^2_{HY,EU}$	0.007^{***}	0.0012
$\hat{\sigma}^2_{VAL}$	0.0073^{***}	0.0026	$\hat{\sigma}^2_{VAL}$	0.024^{***}	0.0052
$\hat{\sigma}^2_{MOM}$	0.0023^{***}	0.0011	$\hat{\sigma}^2_{MOM}$	0.001	0.0028
$\hat{\sigma}^2_{CARRY}$	0.0218^{***}	0.0057	$\hat{\sigma}^2_{CARRY}$	0.009^{**}	0.0068
$\hat{\sigma}^2_{BAB}$	0.0115^{***}	0.0029	$\hat{\sigma}^2_{BAB}$	0.038^{***}	0.0204
$\hat{\sigma}_{M,WM,EU}$	-0.0259^{***}	0.0042			
Wald chi2(6)	47,345		Wald chi2(6)	4,192	
obs.	25,434		obs.	25,839	

Table 17. **Effect of model parameters on the equity allocation**: This table shows the coefficient estimates of a regression of the equity allocation on pension fund characteristics from 2009Q1-2017Q4. The equity allocation is computed as the total AUM in equities divided by the total AUM in fixed income and equities. The pension fund characteristics are the funding ratio, the risk aversion coefficient that we represent with the inverse of the required funding ratio, and the liability duration. Standard errors are in parentheses and clustered at the pension fund level; $^{*}p < 0.10$, $^{**}p < 0.05$, and $^{***}p < 0.01$.

	Equity allocation		
Funding ratio	0.0756***	0.0748***	0.0772***
	[0.0106]	[0.0106]	[0.0106]
Risk aversion	-1.865***	-1.866***	-1.853***
	[0.0401]	[0.0391]	[0.0397]
Liability duration	-0.0015***	-0.0015***	-0.0015***
	[0.0003]	[0.0003]	[0.0003]
Size			0.0038*
			[0.0021]
Corporate			-0.0081**
			[0.0035]
Professional			-0.0200***
			[0.0063]
Constant	0.360***	0.360***	0.367***
	[0.0013]	[0.0013]	[0.0030]
time FE	No	Yes	Yes
obs.	8,648	8,648	8,648
adj. R-squared	0.246	0.275	0.277

Table 18. **Impact of pension fund's characteristics on factor exposures - proxy**: We regress the pension funds' excess returns on the factor returns and the factor returns interacted with the funding ratio, the risk aversion coefficient that we represent with the inverse of the required funding ratio, and the ratio of actives relative to total participants during the period from 2009Q1-2017Q4, where the total equals the active participants and the retirees. Standard errors are in parentheses and clustered at the pension fund level; $^{*}p < 0.10$, $^{**}p < 0.05$, and $^{***}p < 0.01$.

Panel A: Equity returns

	average	funding ratio	risk aversion	% active participants
$\beta^{M,W}$	0.713***	-0.0166	-0.482***	0.0243
	[0.0061]	[0.0513]	[0.1683]	[0.0266]
$\beta^{M,EU}$	0.253***	0.0518	0.208	-0.0027
	[0.0063]	[0.0437]	[0.1644]	[0.0256]
β^{VAL}	0.0263**	-0.0583	0.477	0.0616
	[0.0116]	[0.0929]	[0.3415]	[0.0482]
β^{MOM}	-0.0487***	-0.0064	0.274	0.001
	[0.0080]	[0.0599]	[0.2059]	[0.0330]
β^{CARRY}	0.0165*	0.0794	-0.385	0.0053
	[0.0091]	[0.1146]	[0.2909]	[0.0427]
β^{BAB}	0.0838***	0.0275	-0.0616	-0.0744**
	[0.0153]	[0.0569]	[0.2126]	[0.0330]
obs.	8,851	adj. R-sq.	0.860	

Panel B: Fixed income returns

	average	funding ratio	risk-aversion	% active participants
$\beta^{M,EU}$	2.204***	-0.977***	9.394***	1.561***
	[0.0505]	[0.2358]	[1.3144]	[0.2362]
$\beta^{HY,EU}$	-0.0371***	0.0714*	-0.776***	-0.130***
	[0.0065]	[0.0424]	[0.1504]	[0.0267]
β^{VAL}	-0.157***	0.0261	-0.682	-0.0426
	[0.0187]	[0.0893]	[0.4933]	[0.0789]
β^{MOM}	0.015	-0.0351	1.081***	0.0749
	[0.0118]	[0.0606]	[0.3158]	[0.0518]
β^{CARRY}	-0.557***	0.360**	-3.770***	-0.733***
	[0.0341]	[0.1709]	[0.9128]	[0.1582]
β^{BAB}	-0.0821***	0.142	-1.964***	-0.406***
	[0.0260]	[0.1220]	[0.7088]	[0.1205]
obs.	8,954	adj. R-sq.	0.558	