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* Views expressed are those of the authors and do not necessarily reflect official positions of De Nederlandsche Bank.

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Pension Funds and Drivers of Heterogeneous Investment Strategies*

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Abstract

We use bias-free data to analyse the investment strategies of pension funds with similar objectives by measuring their factor exposures within equity and fixed income portfolios. We find substantial heterogeneity in these factor exposures reflecting annual return differences of $1.31-2.35$ percentage points. Following our mean-variance optimization model, we find that the funding ratio, risk aversion, and liability duration explain 36 percent of this heterogeneity. We attribute the remaining 64 percent to differences in beliefs that pension funds disclose through their contracting of asset management firms. Beliefs therefore 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

Pension funds play a pivotal role in society as many people depend on them for their retirement savings and investments. According to the most recent OECD figures, pension funds around the globe managed USD 32 trillion in 2019.[1] The investments of these pension funds serve a similar objective, namely to finance the current and future liabilities towards their beneficiaries. Understanding what drives pension funds to structure their investments in a particular way is important because 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 after retirement or the contributions being made during the accrual phase. This is particularly relevant because beneficiaries are typically not free to choose a pension fund as it "comes with the job". As a result, most pension funds operate in an environment where they do not have to compete for market share as 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. The 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 strategies across pension funds, the drivers of this heterogeneity, and the effects it has on the expected retirement incomes or pension contributions. We find substantial heterogeneity

[1] `https://stats.oecd.org/`

[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.

in the investment strategies that reflect annual return differences of 1.31−2.35 percentage points. To analyse these differences, 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: funding ratio, risk aversion, and liability duration. Nonetheless, we find that 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 the average annual returns of 0.70−1.50 percentage points. 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 accrue the same retirement income. We show that these differences reflect heterogeneity in beliefs across pension funds that they partially disclose through their choices of the asset management firms that they hire to execute their investment strategies. Our findings have important economic implications, 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 focus of our study is occupational 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 vast majority of the pension funds in the Netherlands use a collective defined-contribution scheme. In such a scheme, beneficiaries accrue benefits, similar to a defined-benefit scheme, that are determined by a formula that accounts for an employee's salary and years of service. However, the scheme also contains features of a defined-contribution scheme because the annual cost-of-living adjustment or indexation is contingent on the pension fund's funding ratio.[4] The proprietary data that we use are the

[3]See the infographic in the Internet Appendix (Figure I.A.1).

[4]This contingent feature works as follows: If the funding ratio, or the ratio of assets over liabilities, is higher than 130 percent, then full indexation will be granted in line with the actual inflation or wage growth. If the funding ratio is below 130 but above 105 percent, partial indexation can be granted. A funding ratio

quarterly asset class returns 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 of biases from self-reporting.

We study investment strategies through factor exposures. Traditionally, the investment 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 factor. 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 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 link objective pension fund characteristics to factor exposures; and third, we measure the differences in the subjective implied beliefs on the factor returns. Along these lines we report the following 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

below 105 percent means no indexation, and if the funding ratio is below 90 percent even a reduction in accrued benefits may be required. This policy ladder shows that in a collective defined-contribution scheme, the benefits depend on investment returns via a pension fund's funding ratio, see also Broeders (2010).

and carry. We also find substantial heterogeneity in both equity and fixed income factor exposures across pension funds.

Second, we show that the objective 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 the case of long-short factors.

Third, we show that the remaining differences in investment strategies can be attributed to differences in the implied beliefs on the expected returns. We infer these subjective implied beliefs by using our theoretical framework and show evidence in favor of this conjecture. We then show that the pension funds disclose 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 liability discount rate, affect investment strategies. In 2007 a fixed discount rate of 4 percent was replaced by the term structure of 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 investment-grade fixed income market and to the low beta factors, and to lower their exposure to the fixed income value and carry factors.

Contributions to the literature

Our paper contributes in different ways to the understanding of the behavior of institutional investors in a regulated setting. In particular we focus on investment behavior related to the underfunding of pension funds, a low interest environment, changes in regulation, and to asset mispricing.

First, we contribute to the literature on the investment decisions of underfunded pension funds by confirming the risk management incentive from Rauh (2009). 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 in pension fund investing the risk management incentive to avoid costly financial distress dominates the incentive to shift risks to the Pension Benefit Guaranty Corporation (PBGC). We extend this study by showing that poorly funded pension funds, that do not have an external guarantee scheme, 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.

Second, we add to the literature by showing that pension funds have a high demand for safe long-term bonds when interest rates are low because of declining funding ratios and when the liability discount rate is linked to the term structure of market interest rates. This finding is in line with the investment behavior of German insurance companies as shown by (Domanski et al. 2017). Our results, and those of (Domanski et al. 2017), contrast with Andonov et al. (2017) and Lu et al. (2019) who show that US public pension funds increase their risk-taking in financial markets when interest rates are lower. This increase is a way that these public pension funds can artificially support their funding ratio because they discount their pension liabilities against the expected returns on their assets.[5]

Third, we add to the literature on the effect of changes in regulation on investment behavior by showing that, when moving from a fixed to a risk-free market-based liability discount rate, pension funds increase the duration of their fixed income portfolios. Greenwood and Vissing-Jorgensen (2018) document that regulatory changes in the liability discount rate that link to market interest rates creates a shock in the demand for long-term bonds from these investors. We extend Greenwood and Vissing-Jorgensen (2018) by showing

[5]This incentive is created through the guidelines of the US Governmental Accounting Standards Board (GASB).

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 duration liability.

Fourth, our study also contributes to the literature that indicates institutional investors contribute to asset mispricing such as in Coval and Stafford (2007), Gutierrez and Kelley (2009), and Dasgupta et al. (2011). In particular, Edelen et al. (2016) find that institutional investors trade contrary to anomalies. Our results support this finding because we find a number of average factor exposures to be negative while those factors that are based on anomalies have positive average returns. We conjecture that the Dutch regulation on the liability discount rate is one driving force behind this negative exposure. For instance, the exposure to the fixed income value and carry factors decreased substantially when the Dutch legislator replaced the fixed discount rate with the risk-free market interest rates in 2007. Consequently, pension funds created a preference for Dutch and German government bonds that resemble the risk-free term structure of interest rates but at the same time have lower value and carry ranks. This regulatory-driven preference may contribute to a negative exposure to the value and carry factors in fixed income.

The remainder of the study is organized as follows: Section II provides a model to derive the optimal portfolio weights and testable implications. A description of the data is given in Section III. In Section IV, we estimate the factor exposures and we analyse the effects of pension fund characteristics 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 and testable implications

To start our analysis, we present a model to derive the optimal portfolio weights within asset classes and to explain the heterogeneity across pension funds. 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 (A) minus the value of its liabilities (L), or its surplus ($A - L$). The pension fund has access to an investable universe of M assets, and its wealth evolves over time as follows:

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

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 $t+1$. We assume that the return dynamics of the liabilities can be replicated by a bond portfolio so that the value of the liabilities at time $t+1$ equals:

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

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.[6] 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]

We normalize the surplus by dividing it by the value of assets to get the following optimization problem:

$$\begin{aligned} \max_{w_{i,t}} \quad & \mathbb{E}_{i,t}\left[u\left(\frac{A_{i,t+1} - L_{i,t+1}}{A_{i,t}}\right)\right] \\ = \quad & \max_{w_{i,t}} \mathbb{E}_{i,t}\left[\frac{A_{i,t+1} - L_{i,t+1}}{A_{i,t}}\right] - \frac{\gamma_i}{2} \mathrm{Var}_t\left[\frac{A_{i,t+1} - L_{i,t+1}}{A_{i,t}}\right], \end{aligned} \tag{3}$$

subject to

[6] In Section VII we will analyse the impact of the regulatory discount rate.

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

$$w_{i,t}'\iota_M \leq c, \qquad w_{i,j,t} \geq 0 \ \forall j, \tag{4}$$

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 in which $c = 1$ typically means that the pension fund cannot invest more than its entire wealth, and $w_{i,j,t}$ is the weight in asset j where $j = 1, ..., M$. Solving (3) results in the following optimal portfolio weights $w_{i,t}^*$ (see derivation in Appendix A):

$$w_{i,t}^* = \underbrace{\frac{\mathbb{E}_{i,t}[r_{t+1}] + \lambda_{i,t}\iota_M + \delta_{i,t}}{\gamma_i \text{Var}_t[r_{t+1}]}}_{\text{speculative portfolio}} + \underbrace{\frac{\text{Cov}_t[r_{t+1}^b\iota_M, r_{t+1}]\psi_{i,t}\iota_M}{\text{Var}_t[r_{t+1}]}F_{i,t}^{-1}}_{\text{hedging portfolio}}, \tag{5}$$

with

$$w_{i,j,t}^* \geq 0, \qquad \delta_{i,j,t} \geq 0, \qquad \delta_{i,j,t}w_{i,j,t}^* = 0 \ \forall j. \tag{6}$$

We assume that each pension fund i has subjective expectations about the expected returns 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.

The solution in (5) shows that the optimal portfolio weights consist of the sum of two components: a speculative and a hedging portfolio. These two components resemble the investment practice of a pension fund. On the one hand, the pension fund invests in bonds and other assets that are highly correlated with its liabilities to "match" the future stream of cash flows being paid to beneficiaries. On the other hand the pension fund invests in assets that offer a risk premium. The higher expected return on these assets can be used to finance the cost-of-living adjustment or indexation. The Lagrange multiplier ensures that the speculative demand decreases if the hedging demand increases, and vice versa.

We cannot directly observe the risk aversion parameter, but we conjecture that it will be inversely related to the "required funding ratio". This 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 has a higher capital requirement. 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).

Unfortunately, we also 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 the factor exposures. In Appendix A we show the implication of the portfolio weights for the factor exposures. We use the factor exposures to formulate the following three testable implications:

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 duration liability 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 that are collected for regulatory purposes by De Nederlandsche Bank. Pension funds report time-weighted returns that take into account dividends or coupons received and the buying and selling in the asset class during the quarter. Total returns are in euros net of transaction costs and exclude the returns from derivative positions. Since 2010, pension funds use standardized principles to compute the returns in accordance with the Global Investment Performance Standards (GIPS). Pension funds separately report the overall portfolio return, the equity portfolio return and the fixed income portfolio return. The sample contains 572 distinct pension funds. Table I.A.2 of the Internet Appendix shows that this sample represents on average 93 percent of the AUM of all Dutch pension funds.

Panel A of Table 1 presents the summary statistics for pension funds' equity and fixed income returns and allocations. 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.[8] The mean excess return on fixed income is 3.89 percent per year with a standard deviation of 10.04 percent. We measure the excess returns against the 3-month Euribor rate. In all of our analyses, we use equally weighted returns. However, there are a few very large industry-wide pension funds in the Netherlands. Therefore, for comparison reasons, Table 1 shows that the value-weighted mean excess return for equities equals 4.80 percent and for fixed income it equals 3.73 percent.

Table 1 also presents the summary statistics on pension fund characteristics. 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

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

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

[Place Table 1 about here]

B. Factors

We now turn to the factors that we will use to explain the time-series and cross-section of returns. Next to market factors, we use the following long-short factors that studies have shown to perform robustly across several asset classes and markets: value, momentum, carry, and low beta (e.g. Asness et al. 2013; Frazzini and Pedersen 2014; Koijen et al. 2018; Baltussen et al. 2021). The value factor for equities is a strategy that goes long in value stocks and short in growth stocks (see, e.g., Fama and French 1993). As fixed income generally does not have measures of book value, the value factor for fixed income is a long position in bonds with a high positive five-year change in the yield and a short position in bonds with a high negative five-year change in the yield, based on de Bondt and Thaler (1985).[9] The momentum factor is defined in the same way for equities and bonds: long in assets with a high 12-month return and short in assets with a low 12-month return (see, e.g., Jegadeesh and Titman 1993). The carry factor goes long in high carry assets and short in low carry assets. Carry is defined as an asset's future return assuming that its price remains the same (see, e.g., Koijen et al. 2018). 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. The low beta factor is similarly defined for stocks and

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

bonds: long in assets with a low exposure to the corresponding market index and short in assets with a high exposure to the market index (see, e.g., Frazzini and Pedersen 2014).

1. Equity factors

Dutch pension funds allocated about 77 percent of their equity portfolio outside Europe over the 2007-2017 period.[10] We therefore include both global and European equity market indices to define the market returns. 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 in euros. Given that the majority of equity holdings are global, we use global long-short factors. We take the returns on the value, momentum, and low beta equity factors from the AQR website and the carry factor returns from Ralph Koijen's website. We convert all these monthly returns to quarterly returns by means of compounding. We assume pension funds fully hedge currency exposures and convert all dollar returns into euros.[11] The factor returns in euros are the dollar factor returns times the gross return on the exchange rate (Koijen et al. 2018). Panel B of Table 1 contains the summary statistics for the equity factor returns.

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. 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 (Maggiori et al. 2020). We therefore use European factors for fixed income, as opposed to global factors for equities. Because

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

[11] 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.

bond returns are largely explained by their 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.[12] European fixed income long-short factors are not available, so we construct the value, momentum, carry, and low beta factors ourselves following the methods of Asness et al. (2013), Koijen et al. (2018), and Frazzini and Pedersen (2014). In Appendix B, we describe the procedure for how we construct the factors. For all factors, we assume the investor fully hedges currency exposures against the euro. Panel B of Table 1 has a summary of the factor returns, and Figure 1 shows the evolution of the long-short fixed income factors over time.[13]

[Place Figure 1 about here]

IV. Factor exposures

In this section, we proceed with the estimation of the (unconditional) factor exposures. In subsection A we present a three-step approach to account for measurement errors in the factor exposures. 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.

[12] 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.

[13] The correlation matrix in Table I.A.4 of the Internet Appendix confirms the well-known stylized fact in the literature of the strikingly strong negative correlation between value and momentum for the European fixed income factors (Asness et al. 2013).

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:

$$r_{i,t}^a - r_t^f = \alpha_i^a + \beta_i^{a\prime} f_t^a + \epsilon_{i,t}^a, \quad \text{for} \quad i = 1, \ldots, N, \tag{7}$$

in which r_t^f is our proxy for the risk-free rate: the Euribor 3-month rate, f_t^a is a vector of six factor returns of length K for asset class a, and $\epsilon_{i,t}^a$ is the idiosyncratic error term with standard deviation σ_i^a. In the remainder of the study, we drop the superscript a to simplify the notations. In Table I.A.5 of the Internet Appendix, we present the estimated betas from the time-series OLS in detail.

Second, we use a random-coefficient model to estimate the priors for the factor exposures. Compared to a standard regression model in which the parameters are fixed to a single value, the random-coefficients model makes possible a cross-sectional variation in the parameters, which is our main concern. We specify this model as follows:

$$\begin{aligned} r_{i,t} - r_t^f &= \alpha_i + \beta_i' f_t + \epsilon_{i,t} \\ &= \alpha + \beta' f_t + v_i' f_t + u_i + \epsilon_{i,t}, \end{aligned} \tag{8}$$

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. We use the regression coefficients of the random coefficients model as the prior distribution in the analysis. Thus, the prior betas are defined as:

$$\beta_i^k \sim N(\hat{\beta}^k, \hat{\sigma}_{\beta^k}^2) \quad \text{for} \quad k = 1, \ldots, K \quad \text{and} \quad i = 1, \ldots, N, \tag{9}$$

in which $\hat{\beta}^k$ is the fixed-effect estimator, and $\hat{\sigma}^2_{\beta^k}$ is the variance in the random effect v_i from Equation (8). The variances in the random effects facilitate the testing for the existence of true heterogeneity in the factor exposures. The exact procedure for estimating the random-coefficients model is in Internet Appendix A.

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:

$$\tilde{\beta}^k_i = \frac{\hat{\beta}^k_i / se(\beta^k_i)^2 + \hat{\beta}^k / \hat{\sigma}^2_{\beta^k}}{1/se(\beta^k_i)^2 + 1/\hat{\sigma}^2_{\beta^k}} \quad \text{for} \quad k = 1, \ldots, K \quad \text{and} \quad i = 1, \ldots, N \tag{10}$$

$$\tilde{\sigma}^2_{\beta^k_i} = \frac{1}{1/se(\beta^k_i)^2 + 1/\hat{\sigma}^2_{\beta^k}} \quad \text{for} \quad k = 1, \ldots, K \quad \text{and} \quad i = 1, \ldots, N, \tag{11}$$

in which $\hat{\beta}^k_i$ is the estimated exposure to factor k from the time-series OLS regressions presented in Equation (7) for pension fund i, and $se(\beta^k_i)$ is the corresponding standard error. Equation (10) shows that the factor exposures of pension funds with less precise sample estimates shrink to the prior. The distribution of the posterior factor exposures shows the heterogeneity across pension funds that is corrected for the measurement error. As a result, the posterior betas are economically interpretable.

Table 2 shows the factor exposures after each of the three steps. We focus the discussion on the posterior factor exposures. For equities the average exposures to the world and European market factors equal 0.67 and 0.27, with standard deviations of 0.18 and 0.15 respectively. 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. Although the standard deviations of the posterior market exposures shrink by about one-half compared to the OLS factors, substantial variation in the market exposures still 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. The average negative momentum and value exposures for equities are consistent with the recent findings for retail investors in, for example, 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, the 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 (see Table I.A.6), 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 2 about here]

B. Heterogeneity in average excess returns

The variation in the factor exposures that we observe has consequences for the average differences in excess returns across pension funds. To determine these differences, we compute the contribution of each of the factors to the average excess returns by using the posterior betas obtained from Equation (10). The contribution of each of the factors is then computed as:

$$\mathbb{E}(r_i^k) = \tilde{\beta}_i^k \lambda^k \quad \text{for} \quad k = 1, \ldots, K \quad \text{and} \quad i = 1, \ldots, N, \tag{12}$$

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 into five equally weighted groups. We then disentangle the contribution of each factor to the average excess returns by using (12). Table 3 has a summary of the results for the equity, fixed income, and the total portfolios.

For equities, we find that taking all factors together, the contribution of the factor exposures to average excess returns ranges from 2.23 to 6.40 percentage points. Pension funds with the highest average excess returns have a return contribution from 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 ranges from 1.66 to −0.05.

For fixed income, taking both market and long-short factors together, the contribution of the factor exposures ranges from 1.91 to 3.95 percentage points. The difference in the contributions of market exposures is larger than for equities and ranges from 1.99 to 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 the value and carry factors.

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 total portfolio. The contribution of the market factor has values that range from 2.74 to 4.04 percentage points, and the contribution of the long-short factor exposures has values that range from −0.53 to 0.51 percentage points.

[**Place Table 3 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 (10):

$$\tilde{\mu}_i = \tilde{\alpha}_i + \tilde{\beta}_i'\lambda \quad \text{for} \quad i = 1, \ldots, N, \tag{13}$$

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 $\mathrm{Cov}(\tilde{\mu}, \tilde{\mu}) = \mathrm{Var}(\tilde{\mu})$, we can divide it by the variance of $\tilde{\mu}$ to get:

$$1 = \frac{\mathrm{Cov}(\tilde{\beta}'\lambda, \tilde{\mu}) + \mathrm{Cov}(\tilde{\alpha}, \tilde{\mu})}{\mathrm{Var}(\tilde{\mu})} = \frac{\sum_{k=1}^{K} \mathrm{Cov}(\tilde{\beta}^{k\prime}\lambda^k, \tilde{\mu}) + \mathrm{Cov}(\tilde{\alpha}, \tilde{\mu})}{\mathrm{Var}(\tilde{\mu})}, \tag{14}$$

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

Table 4 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 the 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 the average excess returns. Value explains 3.67 percent of the variation in the average excess returns, and momentum explains 2.58 percent. This finding is consistent with the highest heterogeneity in the return contribution that we found for the carry and low beta factors. Alpha has negative explanatory power for the 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 the 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 percent 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 4 about here]

V. The effect of a pension fund's characteristics on factor exposures

The previous section shows that there is substantial heterogeneity in the factor exposures across pension funds and that it leads to high differences in the returns. In this section, we analyse the drivers behind these factor exposures that are the pension funds' characteristics from our theoretical framework in Section II. We perform a panel data regression of the funding ratio, the risk aversion, and the liability duration that we interact with the factor returns:

$$r^e_{i,t} \quad = \quad \delta'_0 f_t + \delta'_1 f_t \times \mathrm{F}_{i,t-1} + \delta'_2 f_t \times \gamma_{i,t-1} + \delta'_3 f_t \times \mathrm{D}_{i,t-1} + \epsilon_{i,t}, \tag{15}$$

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 $t-1$, and $\mathrm{D}_{i,t-1}$ is the liability duration for pension fund i at time $t-1$. We demean FR_{it-1}, γ_{it-1}, D_{it-1} such that δ_0 can be interpreted as the average pension fund. The results of this analysis are presented in Table 5.

A. Pension funds' characteristics

1. Funding ratio

For equities, we find that pension funds with a low funding ratio do not have different equity factor exposures (Table 5). For fixed income, we find that pension funds with a low funding ratio have more exposure to the market factor and less exposure to the credit and carry factor. A one standard deviation decrease in the funding ratio (0.16) increases the exposure to the market factor by 0.18 and decreases 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.

Furthermore, the funding ratios of pension funds decline when market interest rates decrease because of the duration gap between assets and liabilities, and when the liability discount rate is linked to market interest rates. Therefore, our finding that underfunded pension funds decrease their exposure to credit risk and increase their exposure to long-term safe bonds is consistent with the behavior of German insurance companies found in Domanski et al. (2017). Andonov et al. (2017) find the opposite result for US public pension funds. This difference is likely because of regulation: the discount rate of US public pension funds is the expected return on assets, while Dutch pension funds use the market interest rates for discounting liabilities. 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.

2. Risk aversion

We use the inverse of the required funding ratio as an implicit measure of the risk aversion, as described in Section II. 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.[14]

3. Liability duration

For equities, pension funds with a long duration liability 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 duration liability

[14]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.

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 duration liability 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.[15]

[Place Table 5 about here]

B. Institutional characteristics

Before moving to the next section, we briefly mention that, motivated by the academic literature, we also study the effects of the size and type of pension funds (corporate, industry-wide, or professional group pension funds) on factor exposures. Table I.A.8 of the Internet Appendix shows the results. We find that large pension funds invest in more global portfolios that is consistent with the view that large pension funds have the means to diversify their equity investments more globally than small pension funds. We also find that corporate pension funds follow the market index more closely as opposed to industry-wide or professional group pension funds. Corporate pension funds may be less willing to deviate from benchmarks, because 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. However, correcting the factor exposures for the size or type of pension fund does not further reduce the heterogeneity in the average returns (Table I.A.9 of the Internet Appendix). We therefore do not take these characteristics into account in the next section where we analyse the

[15] We find similar results when using the ratio of active participants relative to the retirees as a proxy for the liability duration. See Table I.A.7 in the Internet Appendix.

remaining heterogeneity in factor exposures.

VI. Heterogeneity in beliefs

In this section, we first show that the characteristics of pension funds do not fully explain investment strategies and that significant heterogeneity still remains in the factor exposures. We then explain the remaining heterogeneity from differences in implied beliefs on the factor returns. We also show that these beliefs reveal themselves in part via the choice of asset management firms by pension funds.

A. Remaining heterogeneity in factor exposures

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 subsection, 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:

$$\tilde{\beta}^k_{adj,i} = \tilde{\beta}^k_i - \hat{\delta}^k_1 \times \overline{\mathrm{F}}_i - \hat{\delta}^k_2 \times \overline{\gamma}_i - \hat{\delta}^k_3 \times \overline{\mathrm{D}}_i \quad \text{for} \quad k = 1, \ldots, K \quad \text{and} \quad i = 1, \ldots, N. \quad (16)$$

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., $\hat{\delta}^k_1, \hat{\delta}^k_2, \hat{\delta}^k_3 > 0$) when the funding ratio, risk aversion, or liability duration is higher than average, and vice versa.

We redo the analysis from Section IV (subsection B) and Table 6 has a summary of 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 ranges from 3.22 to 3.91 percent, and the contribution of long-short factors ranges from −0.25 to 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.

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.

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 the average excess returns of 1.16 percentage points, and this is equivalent to a difference in expected retirement income of 24 percent. Controversy exists on the performance of long-short factors. 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 6 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 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 a method similar to Shumway et al. (2011). In their work, they aim to detect implied beliefs by assuming that fund managers choose portfolio weights such that they maximize their expected returns over a benchmark while minimizing the tracking error. They show that 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 as follows:

$$\hat{\mu}_i = \Sigma_i(w_i - q_i) \qquad \text{for} \qquad i = 1, \ldots, N, \tag{17}$$

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, and q_i are the benchmark portfolio weights.

We apply a similar method to derive the implied beliefs for our sample of pension funds. 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 implied beliefs across pension funds.

We follow the assumption that pension funds maximize excess returns over a benchmark while minimizing the tracking error for two reasons. First, pension funds hire asset management firms to execute the investment strategy within asset classes. The performance of these asset management firms is evaluated against a benchmark; hence, pension funds, like mutual funds, care about the returns relative to a benchmark (e.g. Broeders and de Haan

2020). Second, pension funds have to hold additional capital based on the tracking error of a portfolio. So there is a regulatory penalty on a high tracking error.[16]

We then move on to derive the implied beliefs from our model in an unconditional setting in Appendix C. The implied beliefs about the expected factor returns for pension fund i is:

$$\hat{\mathbb{E}}_i[r_{t+1}] = \gamma_i \mathrm{Var}[r_{t+1}](\beta_i - \beta^{BM}) - \gamma_i \mathrm{Cov}[r^b_{t+1}\iota_N, r_{t+1}]\psi_i \iota_N F_i^{-1} \quad \text{for} \quad i = 1, \ldots, N, \quad (18)$$

where β_i are the factor exposures of pension fund i and β^{BM} the benchmark exposures that are similar across pension funds.

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

For the benchmark factor exposures β^{BM}, 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 exposures correspond to a passive investor who follows the benchmark exactly.

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-

[16] For details on this specific regulation (in Dutch) see https://www.dnb.nl/voor-de-sector/open-boek-toezicht-sectoren/pensioenfondsen/prudentieel-toezicht/eigen-vermogen/standaard-model/handreiking-actief-beheerrisico-s10-standaardmodel-vereist-eigen-vermogen/.

sectional heterogeneity in implied beliefs across pension funds, the precise magnitude of the average risk aversion coefficient is of less importance.

Table 7 shows the results for the annualized implied beliefs (18) on the expected factor returns. 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 for 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 β^{BM} 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 7 but does not affect the cross-sectional heterogeneity across pension funds.

[Place Table 7 about here]

C. The impact via the choice of asset management firms

In this subsection, we address the question of whether these implied beliefs are intentional choices by 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, each quarter the pension funds do report the name of the asset management firm that executes at least 30 percent of the total AUM on behalf of the pension fund. 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.[17] 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

[17]For confidentiality reasons, we cannot disclose the names of the asset management firms in our paper.

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. Del Guercio and Tkac 2002; Goyal and Wahal 2008). Once an asset management firm is selected the mandate is agreed on 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 the period from 2009Q2−2017Q4. A new hire means that we observe a different asset management firm in the current quarter compared to the previous. These observations result in a total of ten asset management firms that gained new business from 59 of the 350 Dutch pension funds that are in our sample, which is equivalent to 17 percent of the pension funds. We subsequently run the following regression:

$$r_{i,t}^e = \delta_0' f_t + \delta_1' (f_t \times \mathrm{AM}_{i,t-1}') \iota_{10} + \epsilon_{i,t}, \tag{19}$$

in which $\mathrm{AM}_{i,t-1}$ 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.[18]

Table 8 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 allocation to global equity and to increase their

[18] The regression results are similar in statistical significance and economic magnitude when we include the pension fund characteristics described in Equation (15).

allocation to European equities. Pension funds that switch 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, 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. However, we still find statistically 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 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. Furthermore, this is consistent with the findings in Del Guercio and Tkac (2002) who show that quantitative performance variables have a much lower explanatory power in explaining the flows of 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 8 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. For pension funds, one of the key channels through which regulations affect investment strategies is the liability discount rate (Andonov et al. 2017). Although finance theory argues that risk-free market interest rates are the applicable discount rates for guaranteed pension benefits to exclude arbitrage (e.g. Brown and Wilcox 2009; Novy-Marx and Rauh 2009), we observe that 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 the return on assets (Andonov et al. 2017).[19] 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. Under such a discount rule, liabilities artificially contain no interest rate risk and a liability-replicating portfolio does not exist: there are no bonds that have exactly a 4 percent return under all states of the world. Furthermore, before 2007 there were no risk-based minimum funding requirements. However, new 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. Consequently, the present discounted value of liabilities fluctuates significantly with changes in the market interest rates. Furthermore, the new regulatory framework also includes risk-based funding requirements. This requirement is derived from a well-known value-at-risk (VaR) concept, in which risk is measured as the mismatch between the assets and liabilities. Pension funds' investment strategies affect the

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

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 9 shows the results. We observe a large change in the exposure to the investment-grade 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 and reflects that they allocated more to long-term bonds. This finding is consistent with our theoretical framework, because the 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 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 9 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'

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

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. Pension fund's characteristics only partially explain the 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 argue that liability-driven investors can use the approach in this study for strategic investment decision-making. Our approach makes a distinction between a hedging demand and a speculative demand, that we measure through factor exposures. While the liabilities of a defined-benefit or a collective defined-contribution pension fund can be measured objectively, a crucial part of 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 them whatsoever. Therefore an import fiduciary duty rests on liability-driven investors to invest in the best interest of their beneficiaries.

Appendix

A Model derivation

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

$$\max_{w_{i,t}} = \max_{w_{i,t}} \mathbb{E}_t\left[\frac{A_{i,t+1}-L_{i,t+1}}{A_{i,t}}\right] - \frac{\gamma_i}{2}\mathrm{Var}_{i,t}\left[\frac{A_{i,t+1}-L_{i,t+1}}{A_{i,t}}\right], \tag{20}$$

subject to

$$w'_{i,t}\iota_M \leq c, \tag{21}$$

$$w_{i,j,t} \geq 0 \;\; \forall j, \tag{22}$$

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:

$$\begin{aligned}\mathcal{L}(w_{i,t},\lambda_{i,t}) &= 1 + w'_{i,t}\mathbb{E}_{i,t}[r_{t+1}] - \Big(1+\psi_{i,t}\mathbb{E}_{i,t}[r^b_{t+1}]\Big)F^{-1}_{i,t} \\ &- \frac{\gamma_i}{2}\Big(w'_{i,t}\mathrm{Var}_t[r_{t+1}]w_{i,t} + \psi^2_{i,t}\mathrm{Var}_t[r^b_{t+1}]F^{-2}_{i,t} - 2w'_{i,t}\mathrm{Cov}_t[r^b_{t+1}\iota_M, r_{t+1}]\psi_{i,t}\iota_M F^{-1}_{i,t}\Big) \\ &+ \lambda_{i,t}(w'_{i,t}\iota_M - c) + \delta'_{i,t}w_{i,t}. \end{aligned} \tag{23}$$

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

$$\begin{aligned}\frac{\partial\mathcal{L}(w_{i,t},\lambda_{i,t})}{\partial w_{i,t}} &= \mathbb{E}_{i,t}[r_{t+1}] - \gamma_i\mathrm{Var}_{i,t}[r_{t+1}]w_{i,t} + \gamma_i\mathrm{Cov}_t[r^b_{t+1}\iota_M, r_{t+1}]\psi_{i,t}\iota_M F^{-1}_{i,t} \\ &+ \lambda_{i,t}\iota_M + \delta_{i,t} = 0, \end{aligned} \tag{24}$$

$$\frac{\partial\mathcal{L}(w_{i,t},\lambda_{i,t})}{\partial \lambda_{i,t}} = w'_{i,t}\iota_M - c = 0. \tag{25}$$

This results in the optimal weights (5):

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

with $\lambda_{i,t}$:

$$\lambda_{i,t} = \frac{c - \left(\frac{\mathbb{E}_{i,t}[r_{t+1}]+\delta_{i,t}}{\gamma_i \mathrm{Var}_t[r_{t+1}]}\right)' \iota_M - \left(\frac{\mathrm{Cov}_t[r_{t+1}^b \iota_M, r_{t+1}]\psi_{i,t}\iota_M}{\mathrm{Var}_t[r_{t+1}]} F_{i,t}^{-1}\right)' \iota_M}{\left(\frac{\iota_M}{\gamma_i \mathrm{Var}_t[r_{t+1}]}\right)' \iota_M}. \tag{25}$$

We show the implication of portfolio weights for factor exposures next. The exposure of the portfolio return r^P to the return on the k^{th} factor r^k is measured as:

$$\beta^k = \frac{\mathrm{Cov}(r^P, r^k)}{\mathrm{Var}(r^k)}. \tag{26}$$

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

$$\beta^k = \frac{\mathrm{Cov}(r^P, r^{k,L} - r^{k,S})}{\mathrm{Var}(r^{k,L} - r^{k,S})} = \frac{\mathrm{Cov}(r^P, r^{k,L})}{\mathrm{Var}(r^{k,L} - r^{k,S})} - \frac{\mathrm{Cov}(r^P, r^{k,S})}{\mathrm{Var}(r^{k,L} - r^{k,S})}, \tag{27}$$

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:

$$r^P = w_V r^V + w_G r^G, \tag{28}$$

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:

$$\beta^{V-G} = \frac{\text{Cov}(r^P, r^V - r^G)}{\text{Var}(r^V - r^G)} = \frac{(w_V - w_G)\sigma_V^2(1-\rho_{V,G})}{\text{Var}(r^V - r^G)} > 0 \tag{29}$$

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.

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 I.A.3 in the Internet Appendix B. 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:

$$P_{i,t}^{\tau,syn} = \frac{1}{1 + r_{i,t}^f} \frac{1}{(1 + y_{i,t})^T}, \tag{30}$$

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

$$P^{\tau-1,syn}_{i,t+1} = \frac{1}{(1 + y_{i,t+\tau})^{T-\tau}}, \tag{31}$$

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

$$r^{syn}_{i,t} = \Big(\frac{(1 + r^f_{i,t})(1 + y_{i,t})^T}{(1 + y_{i,t+\tau})^{T-\tau}} - 1\Big) \times \Big(1 + \frac{e_{i,t+1} - e_{i,t}}{e_{i,t}}\Big) \tag{32}$$

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:

$$w^S_{it} = c_t(\text{rank}(S_{it}) - \sum_{i=1}^{J} \text{rank}(S_{it})/J), \quad \text{where } S \in (\text{value, momentum, carry, low beta}). \tag{33}$$

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):

$$C_{it} = \frac{(1+y_{i,t}^{T})^{T}}{(1+r_{i,t}^{f})(1+y_{i,t}^{T-\tau})^{T-\tau}}. \tag{34}$$

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

$$\hat{\beta}_i = \hat{\rho}\frac{\hat{\sigma}_i}{\hat{\sigma}_m}, \tag{35}$$

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:

$$r_t^S = \sum_{i=1}^{J} w_{it-1}^S r_{it}^{syn}, \quad \text{where } S \in (\text{value, momentum, carry}). \tag{36}$$

The factor return for low beta is constructed as:

$$r_t^{\mathrm{S}} = \frac{1}{\beta_{t-1}^L}(r_t^L - r_t^f) - \frac{1}{\beta_{t-1}^H}(r_t^H - r_t^f), \quad \text{where } S \in (\text{low beta}), \tag{37}$$

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).

C Deriving implied beliefs from the model

To derive implied beliefs on factor returns, we apply a similar methodology as 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:

$$\mu_i \approx \gamma_i \delta_i \Sigma_i (w_i - q_i) - \lambda \mathbf{1} \qquad \text{for} \qquad i = 1, \ldots, N, \tag{38}$$

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:

$$\hat{\mu}_i = \Sigma_i (w_i - q_i) \qquad \text{for} \qquad i = 1, \ldots, N. \tag{39}$$

We can apply this framework to our model in Section II. 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:

$$p(\mu_0) \sim N(\mu, \Sigma). \tag{40}$$

Solving the Lagrange in Equation (23) in an unconditional setting, replacing w_i with $w_i - q_i$, and applying the assumptions above to (38), we can derive the implied beliefs about the expected factor returns for pension fund i as:

$$\hat{\mathbb{E}}_i[r_{t+1}] = \gamma_i \text{Var}[r_{t+1}](\beta_i - \beta^{BM}) - \gamma_i \text{Cov}[r^b_{t+1}\iota_N, r_{t+1}]\psi_i \iota_N F_i^{-1} \quad \text{for} \quad i = 1, \ldots, N. \tag{41}$$

where we use the factor exposures instead of the portfolio weights such that $w_i = \beta_i$ and benchmark exposures instead of benchmark weights such that $q_i = \beta^{BM}$.

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Table 1. **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 2. **Factor exposures**: This table displays the cross-sectional means and standard deviations of the OLS betas from Equation (7), the prior betas from Equation (8), and the posterior betas from Equation (10). 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 3. **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 4. **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 (14). 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 5. **Effect of pension fund's characteristics on factor exposures**: This table shows the coefficient estimates of Equation (15): 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. 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 6. **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) and returns corrected for the pension fund characteristics (Panel B). Panel Cuses the same specification as Panel B 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 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 7. **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 (18). 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 8. **Effect of asset management firm changes on factor exposures**: This table shows the coefficient estimates of Equation (19): 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 9. **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 (10) 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.

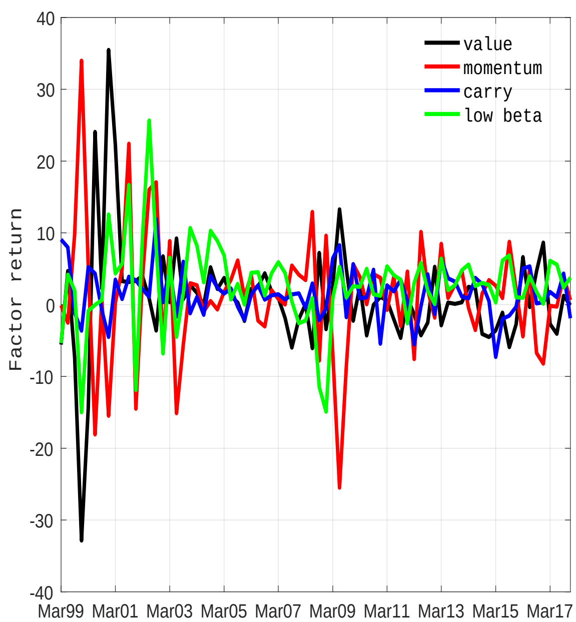
Panel A: Equity

	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^{***}

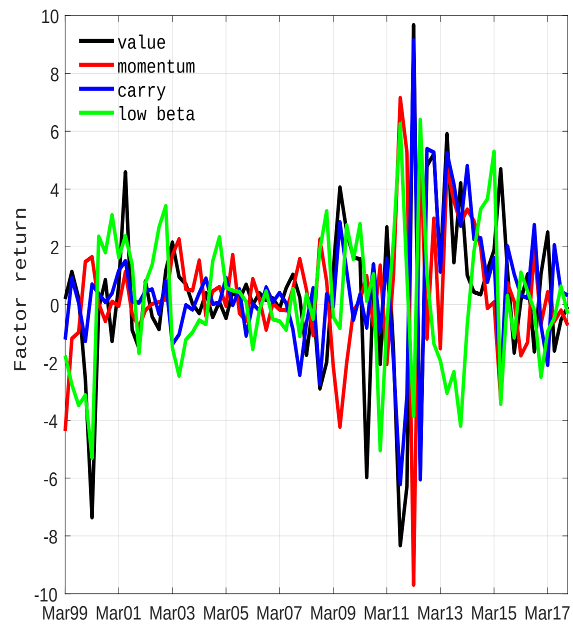
Panel B: Fixed income

	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

Internet Appendix

A Random-Coefficients Model

We make the following assumptions when estimating the regression in Equation (8):

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

$$G = \mathbb{E}(v_k v_j') = \begin{cases} \sigma^2_{\beta^k} & \text{for} \quad j = k \\ \sigma_{\beta^k \beta^j} & \text{for} \quad j \neq k \end{cases} \tag{42}$$

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]

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 (8) in vector notation:[22]

$$r_i^e = \alpha \iota_T + \beta' f + v_i' f + u_i + \epsilon_i, \tag{43}$$

[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.

[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.

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:

$$\operatorname{Var}\begin{bmatrix} \alpha_i \\ v_i^1 \\ .. \\ v_i^K \\ \epsilon_i \end{bmatrix} = \begin{bmatrix} \sigma_\alpha^2 \iota_T\ \iota_T' & 0 & 0 & 0 & 0 \\ 0 & \sigma_{\beta^1}^2 \iota_T \iota_T' & \sigma_{\beta^1\beta^2} \iota_T \iota_T' & 0 & 0 \\ 0 & \sigma_{\beta^2\beta^1} \iota_T \iota_T' & \ddots & 0 & 0 \\ 0 & 0 & 0 & \sigma_{\beta^K}^2 \iota_T \iota_T' & 0 \\ 0 & 0 & 0 & 0 & \sigma_\epsilon^2 \mathbf{I}_T \end{bmatrix}. \tag{44}$$

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

$$V = \operatorname{Var}[r_i^e | f] = \sigma_\alpha^2 \iota_T\ \iota_T' + \sigma_{\beta^1}^2 f^1 f^{1'} + 2\sigma_{\beta^1\beta^2} f^1 f^{2'} + \sigma_{\beta^2}^2 f^2 f^{2'} + ... + \sigma_{\beta^K}^2 f^K f^{K'} + \sigma_\epsilon^2 \mathbf{I}_T. \tag{45}$$

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

$$L_i(\alpha, \beta, \sigma_\alpha^2, \sigma_{\beta^1}^2, ..., \sigma_{\beta^K}^2, \sigma_\epsilon^2 | r_i^e) = -\frac{1}{2}\{T \log(2\pi) + \log|V| + (r_i^e - \alpha\iota_T - \beta' f)' V^{-1} (r_i^e - \alpha\iota_T - \beta' f)\}. \tag{46}$$

Then, the total log-likelihood equals:

$$L(\alpha, \beta, \sigma_\alpha^2, \sigma_{\beta^1}^2, ..., \sigma_{\beta^K}^2, \sigma_\epsilon^2 | r^e) = -\frac{1}{2}\{NT \log(2\pi) + N \log|V| + \sum_{i=1}^{N} (r_i^e - \alpha\iota_T - \beta' f)' V^{-1} (r_i^e - \alpha\iota_T - \beta' f)\}. \tag{47}$$

We now turn to a detailed description of the estimation results described in Table I.A.6. 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).

B Additional tables

Table I.A.1. **Glossary of symbols**: This table summarizes the main symbols in this study.

Symbol	*Description*
A	Asset value
AM	Vector of asset management firms
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
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^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
β^{BM}	Benchmark factor exposures
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 I.A.2. **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 I.A.3. **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 I.A.4. **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 I.A.5. **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 (7). 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 I.A.6. **Prior factor exposures**: This table shows the coefficient estimates and corresponding standard errors for the random-coefficients model in Equation (8) 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 I.A.7. **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	

Table I.A.8. **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. 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 I.A.9. **Heterogeneity of average excess returns correcting for institutional factors**: 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) and returns corrected for the pension fund characteristics and institutional factors: size and pension fund type (Panel B). 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

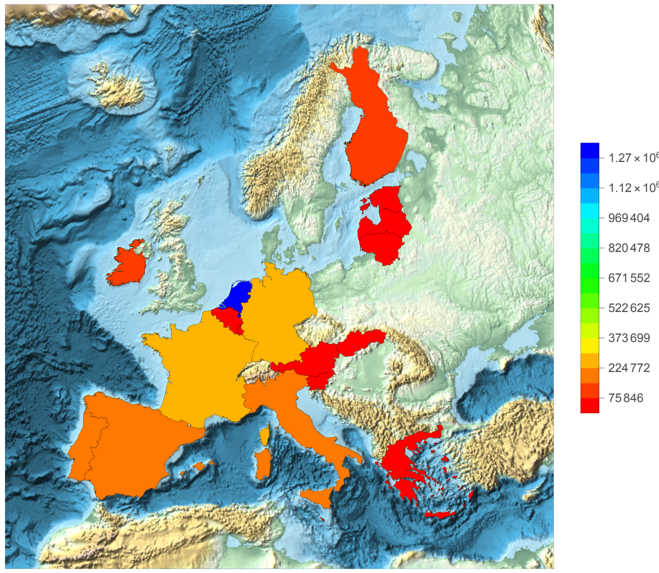
	0-20th	20-40th	40-60th	60-80th	80-100th	diff.
All factors	2.21	3.02	3.51	3.93	4.56	2.35
Market factors	2.74	3.24	3.46	3.78	4.04	1.30
Long-short factors	-0.53	-0.21	0.05	0.15	0.51	1.04

Panel B: Returns corrected for pension fund characteristics 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

C Additional figures

Figure I.A.1. **AUM pension assets euro area**: This figure shows the total assets in million EUR in funded and private pension plans in the euro area (OECD 2019).



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