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Liability-Driven Investors

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Abstract

We find large heterogeneity in the investment strategies of liability-driven investors by using data on occupational pension funds. We measure investment strategies through their factor exposures within equity and fixed income portfolios. In line with our model that solves a mean-variance optimization problem of assets minus liabilities, we find that the funding ratio, risk-aversion, and liability duration explain part of the heterogeneity in the factor exposures. The remaining heterogeneity that is not explained by the model reflects an annual expected return difference of 1.04 percentage points between the pension funds with the highest and those with the lowest factor exposures. This is equivalent to a difference in expected retirement income of 24 percent. We also find a large time variation in the fixed income factor exposures due to active changes in country allocations. This variation shows that liability-driven investors adjust their investment strategies following innovations in the news about assets with similar characteristics as their liabilities.

Keywords: factor exposures, liabilities, pension funds, regulations, returns.
JEL classifications: G11, G23

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I. Introduction

Liability-driven investors make professional investment decisions to finance the future liabilities to their beneficiaries. These investors generally have broadly diversified investment portfolios with equities, fixed income securities, real estate, and alternative assets. Key liability-driven investors are defined-benefit pension funds, insurance companies, and endowment funds. By contrast, mutual funds operate from an "asset-only" perspective and typically, but not exclusively, specialize in an asset class, market, or investment style. Mutual funds pool money from a group of investors with the aim of making returns through the buying and selling of securities. The investors are the shareholders of mutual funds.

Liability-driven investors play a pivotal role in society as many people depend on their investment performance. Understanding how liability-driven investors finance their liabilities is important as the financing may have a substantial effect on beneficiaries' purchasing power. While many papers analyze mutual funds' investment strategies, for example, Grinblatt et al. (1995), Brown and Goetzmann (1997), and Chan et al. (2002), so far only a few have analyzed the investment strategies of liability-driven investors. The lack of access to comprehensive and detailed data on this type of investor is the main reason for the limited number of studies. Exceptions are Rauh (2009) and Andonov et al. (2017) who study pension funds' risky asset allocations.[1]

The primary objective of this paper is to provide a rigorous analysis of liability-driven investors' investment strategies that is supported by a model that solves a mean-variance optimization problem of assets minus liabilities. We use unbiased proprietary data on occupational defined-benefit pension funds. Instead of analyzing risky asset allocations, we measure investment strategies more granularly through the factor exposures within equity portfolios. In addition, we also thoroughly analyze fixed income portfolios this way. We find that there is a large variation in investment strategies that cannot be explained by

[1] Lakonishok et al. (1992), Blake et al. (1999), Tonks (2005), Goyal and Wahal (2008), and Blake et al. (2013) also study the investment decisions of pension funds, but the focus in these papers is on the portfolio managers hired by the pension funds.

differences in the funding ratio, risk-aversion, and liability structure of the pension funds. This heterogeneity reflects economically sizable differences in expected annual returns of 1.04 percentage points between the pension funds with the highest and those with the lowest factor exposures. This is equivalent to a difference in expected retirement income of 24 percent over a 40-year accrual phase. These differences in expected returns, and thus in beneficiaries' expected purchasing power, are important because a pension scheme is often linked to an employment contract. In such a case, employees have no freedom to choose their own pension fund.

Globally 50 percent of all occupational retirement savings is in defined-benefit pension funds (Willis Towers Watson 2019). The object of our study is occupational defined-benefit pension funds in the Netherlands. The Dutch occupational pension system is economically important because it is large in terms of total assets under management (AUM). In 2018, the AUM equaled approximately 1.4 trillion euros, and the Dutch system represented 53 percent of the total assets of pension funds in the euro area, (OECD 2019). The proprietary data that we use are the quarterly returns of asset classes over the period from 1999 to 2017, and the return computations are based on the Global Investment Performance Standards (GIPS) as of 2010. The reporting requirements are mandatory, and the data are therefore free from self-reporting biases.

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 asset classes. This literature shows that factors based on a particular signal perform robustly across countries and asset classes. Prime examples include momentum and value (Asness et al. 2013), low beta (Frazzini and Pedersen 2014), and carry (Koijen et al. 2018). We use the existing global factors for equities: the market, value, momentum, carry, and low beta. For fixed income, we construct European factors as the pension funds in our sample primarily invest in euro dominated bonds, which confirms the currency bias in Maggiori et al. (2019). 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 take three sequential steps to analyze the investment strategies of pension funds. In Section IV, we estimate the cross-sectional average and heterogeneity in unconditional factor exposures of pension funds for both equities and fixed income portfolios. Heterogeneous factor exposures reflect the differences in investment strategies which, in turn, lead to differences in performance across pension funds. In Section V, we research the pension fund's characteristics that drive the heterogeneity in factor exposures by following our theoretical framework that solves a mean-variance optimization problem of assets minus liabilities that is described in Section II. Motivated by the academic literature, we also study the effects of size and delegated asset managers on factor exposures. In Section VI, we examine the time variations in the conditional factor exposures for both equities and fixed income portfolios. To study active portfolio repositioning, we link the changes in factor exposures to changes in country allocations. This analysis provides information about the extent to which pension funds change their investment strategies over time.

We report the following key results: First, we show in Section IV that the average pension fund has a stock market beta lower than one and a fixed income market beta larger than one. Further, for both equities and fixed income the average pension fund has a positive exposure to low beta but a negative exposure to value and carry. These negative exposures are inconsistent with our model and point to an inefficiency, because the negative factor exposures have an aggregate negative contribution to expected annual returns of 0.47 percentage points. This is equivalent to expected retirement income that is 11 percent lower over a 40-year accrual phase.

Second, we find substantial heterogeneity in both equity and fixed income factor exposures across pension funds. A variance decomposition reveals that the heterogeneity in market exposures is the most important driver of the heterogeneity in returns for both asset classes, followed by low beta, value, and carry respectively. In Section V, we study the drivers of the heterogeneity in factor exposures. First, we assess the effects of the funding ratio, risk-aversion (represented as the inverse of the required funding ratio), and liability duration (represented as the ratio of active participants relative to the total of active participants and retirees) on factor exposures that come from our theoretical framework. We make the following observations: First, we find no substantial relation between the funding ratio and equity factor exposures. By contrast, for fixed income we find that pension funds with a high funding ratio have less exposure to the investment-grade market factor but take more credit risk. Second, pension funds for which our proxy of risk-aversion is higher have lower exposure to the equity market. For fixed income, these pension funds have higher exposure to the investment-grade market factor but lower exposure to the credit factor and lower aggregate exposure to the long-short factors. Third, pension funds with a long liability duration, that is, a high fraction of active participants, do not differ in their equity exposures. For fixed income, a long liability duration results in a higher exposure to the investment-grade market factor but a lower exposure to credit, carry, and low beta. Overall, these findings are consistent with the predictions of our model: 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.

Next to the variables predicted by the model and motivated by the academic literature, we also study pension funds' sizes and asset managers. First, size as measured by assets under management results in more globalized portfolios and higher credit risk but does not have an effect on the exposures to long-short factors. Second, for both equity and fixed income, asset managers do play a nontrivial role. The five most often delegated asset managers under contract amplify factor exposures. For instance, for equity, the exposure to the value factor may decrease by 0.05 or increase by 0.21 depending on the delegated asset manager. For fixed income, the delegated asset manager may increase the exposure to value by 0.10 or 0.14.

Pension funds can employ asset managers who may have different beliefs about factors. As shown in Binsbergen et al. (2008), the optimal solution to the mean-variance optimization problem for a pension plan is generally different from the combination of the mean-variance efficient portfolios of the asset managers.

As a final explanation for the heterogeneity in the factor exposures that are not predicted by the model we derive pension funds' implied beliefs about the factor returns. For equities we show that pension funds particularly differ in their implied beliefs about the global market factor, the European market factor, and the value factor. For fixed income the largest heterogeneity in beliefs is in the credit factor and the low beta factor.

The heterogeneity in factor exposures has consequences for the expected returns and thus on the expected performance differences across pension funds. On a total portfolio level, the contribution of all factors to overall expected returns is 2.26 percentage points higher for the pension funds with the highest factor exposures compared to those with the lowest. The contribution of the factors unrelated to differences in the funding ratio, risk-aversion, and liability structure is 1.04 percentage points higher for the pension funds with the highest exposures compared to those with the lowest. This is indeed an economically sizable effect: a 1.04 percentage point lower annual return over the accrual phase decreases expected retirement income by 24 percent or increases contributions by 31 percent to get the same income.

Further, in Section VI, we observe that the time variations in the conditional factor exposures for equities are minor. However, the time variation for fixed income is much larger. The average long-short factor exposures can get as low as -0.8 (for the value factor exposure in 2012) and as high as 0.9 (for the carry and momentum factor exposures in 2011). We also show that these large changes in factor exposures are due to active portfolio repositioning. For instance, pension funds increased their exposures to vulnerable countries (Greece, Ireland, Italy, Portugal, and Spain) in the aftermath of the global financial crisis. However, during the sovereign debt crisis, they substantially decreased their holdings in vulnerable countries. For instance, the average allocation to Greece went down from approximately 250 million in mid 2011 to only 2 million in the second half of 2012 and for Spain the average allocation of 1,000 million went down to approximately 500 million over the same period (nominal values). These allocations show that pension funds adjust their investment strategies following innovations in the news about assets with similar characteristics as their liabilities.

Literature review

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

Andonov et al. (2017) find that US public pension funds increase their risk-taking in financial markets when the interest rates are lower. This increase is a way these public pension funds can artificially support their funding ratio because they discount pension liabilities against the expected returns on their assets.[2] We add to this work by analyzing the investment behavior of pension funds in a regulatory environment in which pension funds are not free to choose their own discount rate, but like US private pension funds and

[2] This incentive is created through the US GAAP accounting standards.

Canadian and other European pension funds, link to the term-structure of market interest rates.

Greenwood and Vissing-Jorgensen (2018) show that regulatory changes in the liability discount rate that link to market interest rates affect the yield curve due to a shock in demand for long-term bonds from these investors. Our results also support the view that the liability discount rate shapes pension funds' investment behavior, in particular within fixed income portfolios. Our results show that pension funds prefer safe long-term bonds, particularly during crises, as well as securities denominated in euros. More importantly, we add to Greenwood and Vissing-Jorgensen (2018) by showing 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 high liability duration.

Our work also relates to the investment behavior of long-term investors during periods of low interest rates. Next to Andonov et al. (2017), Lu et al. (2019) also find that US public pension funds increase their risk-taking during periods of low interest rates. Our results seem to contradict their finding, as pension funds in our study increase their exposure to the investment-grade fixed income index, while slightly lowering their exposure to credit risk. Again, a logical explanation for this contradiction is that the liability discount rates of US public pension funds link to the expected returns on their assets, while they link to market interest rates for Dutch pension funds. Our results are therefore more in line with the investment behavior of German insurance companies that demand more safe long-term bonds when interest rates are low (hunt for duration), as shown by Domanski et al. (2017).

Our paper also contributes to the literature that assesses the effect of institutional investors on asset prices. For example, Coval and Stafford (2007), Gutierrez and Kelley (2009), and Dasgupta et al. (2011) present evidence that institutional investors contribute to mispricing. In particular, Edelen et al. (2016) find that institutional investors trade contrary to anomalies. Our results support this finding because we find many factor exposures to be negative on average. We conjecture that regulation with respect to the liability discount rate is a driving force behind the preferences for assets in the short leg of the anomaly. For instance, the exposure of pension funds during the euro sovereign debt crisis to the bond carry factor decreased and became strongly negative because of an increased demand for German and Dutch government bonds.

The remainder of the paper is organized as follows. Section II provides a model to derive optimal portfolio weights. A description of the data is given in Section III. In Section IV, we analyze unconditional factor exposures, and we link pension fund characteristics to factor exposures in Section V. In Section VI we analyze conditional factor exposures. Section VII concludes.

II. Motivating model

In this section we present a model to derive the factor exposures and to explain the heterogeneity across pension funds. Our theoretical framework considers the derivation of factor exposures from the perspective of a pension fund.[3] First, we derive the optimal portfolio weights for a mean-variance investor who optimizes its surplus, that is, the value of assets minus that of the liabilities, subject to borrowing and short-sale constraints. Starting with portfolio weights allows us to closely map the model to the existing mean-variance portfolio theory (Markowitz 1952) and to include borrowing and short-sale constraints that are typically applicable to liability-driven investors. Second, we show the implication of the portfolio weights for factor exposures.

We start with the liability structure. A pension fund pays benefits B_{t+h} to its participants in period $t + h$. These benefits can in practice take any value, but because our paper only considers defined benefit pension funds, we assume that benefits are known at time t. We also assume that the pension fund has a large enough number of participants such that idiosyncratic longevity risk is fully diversified. The present discounted value of all future

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

benefit payments is given by:

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

in which r_t^h is the discount rate as observed on time t for maturity $t + h$. Discount rates vary widely across jurisdictions. For instance, under the US Government Accounting Standards Board (GASB) guidelines, public pension funds are partially free to discount their liabilities at the expected rate of return on the assets (Andonov et al. 2017).[4] By contrast, US corporate pension funds use the yield on high-quality corporate bonds. In our case, pension funds in the Netherlands used a fixed discount rate of 4 percent until 2007. However, the regulations introduced in 2007 required Dutch pension funds to use the risk-free term structure of market interest rates based on the euro swap curve as the discount rate (Broeders et al. 2020). Finance theory argues that risk-free market interest rates are indeed the applicable discount for guaranteed pension benefits to exclude arbitrage (e.g. Brown and Wilcox 2009; Novy-Marx and Rauh 2009).[5] The value of the liabilities at time $t + 1$ is then defined as follows:

$$L_{t+1} = \left(1 + r_{t+1}^L\right) L_t \approx \left(1 + \psi r_{t+1}^b\right) L_t, \tag{2}$$

in which r_{t+1}^L is the liability return that in turn is approximated by the return on a set of risk-free bonds r_{t+1}^b times ψ that is the duration of pension liabilities over the duration of the set of bonds. The value of ψ is typically larger than one because the duration of pension liabilities is (much) larger than the average duration of bonds in the market.

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

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

[5] The term structures of interest rates are based on safe assets that are affected by a convenience yield, as recently shown in van Binsbergen et al. (2019), and are therefore not entirely risk-free. However, the existence of a convenience yield does not affect the main mechanisms in our model.

follows:

$$A_{t+1} = \Big(1 + w_t' r_{t+1}\Big) A_t, \tag{3}$$

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

$$\begin{aligned} \max_{w_t} \quad & \mathbb{E}_t \left[u \left(\frac{A_{t+1} - L_{t+1}}{A_t} \right) \right] \\ = \quad & \max_{w_t} \mathbb{E}_t \left[\frac{A_{t+1} - L_{t+1}}{A_t} \right] - \frac{\gamma}{2} \mathrm{Var}_t \left[\frac{A_{t+1} - L_{t+1}}{A_t} \right], \end{aligned} \tag{4}$$

subject to

$$w_t' \iota_N \leq c, \tag{5}$$

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

in which γ captures the pension fund's time invariant risk aversion parameter, ι_N is a vector of ones with length N, and c is a constant that defines the constraint on the sum of the weights where typically $c = 1$ that means the pension fund cannot invest more than its entire wealth. Solving (4) for the portfolio weights w_t results in (see derivation in Appendix A):

$$w_t^* \;=\; \underbrace{\frac{\mathbb{E}_t[r_{t+1}] + \lambda_t \iota_N + \delta_t}{\gamma \mathrm{Var}_t[r_{t+1}]}}_{\text{speculative portfolio}} + \underbrace{\frac{\mathrm{Cov}_t(r^b_{t+1}\iota_N, r_{t+1})\psi\iota_N}{\mathrm{Var}_t[r_{t+1}]} F_t^{-1}}_{\text{hedging portfolio}}, \tag{7}$$

with

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

The funding ratio is defined as $F_t = \frac{A_t}{L_t}$, λ_t is the Lagrange multiplier for the restriction that $w_t' \iota_N = c$, and δ_t consists of the Kuhn-Tucker multipliers for the restrictions that the portfolio weights are nonnegative. If the Lagrange multiplier is binding, λ_t equals:

$$\lambda_t = \frac{c - \left(\frac{\mathbb{E}_t[r_{t+1}] + \delta_t}{\gamma \mathrm{Var}_t[r_{t+1}]}\right)' \iota_N - \left(\frac{\mathrm{Cov}_t(r^b_{t+1} \iota_N, r_{t+1}) \psi \iota_N}{\mathrm{Var}_t[r_{t+1}]} F_t^{-1}\right)' \iota_N}{\left(\frac{\iota_N}{\gamma \mathrm{Var}_t[r_{t+1}]}\right)' \iota_N}. \tag{9}$$

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

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

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

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

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

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

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

in which w_V is the portfolio weight of value stocks and r^V is the corresponding return, w_G is the portfolio weight of growth stocks and r^G is the corresponding return. In this example, lets 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, i.e. $\rho_{V,G} < 1$. For a beta neutral factor we further have that the volatility of the value stock is approximately equal to that of growth stocks, i.e. $\sigma_V \approx \sigma_G$. This condition results in the following factor exposure:

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

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

A. *Model implications*

The optimal solution in (7) allows us to infer how pension fund characteristics and factor return characteristics drive factor exposures. We summarize the model implications here.

Speculative portfolio

1. For the highest risk averse pension fund ($\gamma \to \infty$), the speculative demand for factors goes to zero.

Hedging portfolio

1. A positive covariance between the liability and a factor return ($\text{Cov}_t(r^b_{t+1}, r^k_{t+1}) > 0$) leads to a positive factor demand from a liability hedging perspective.

2. A longer liability duration, that is, a higher ψ, means a higher hedging demand.

3. A lower funding ratio F_t increases the hedging demand.

Combined effects

1. Speculative demand decreases if hedging demand increases and the borrowing constraint is binding. This condition means that demand for factors uncorrelated with the liability return decreases if the hedging demand increases.

B. Testable implications

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

In our empirical analysis, we use an investment-grade fixed income market index to represent the return on the set of bonds r^b_{t+1}.[6] Further we use the following factors for fixed income: high yield index, value, momentum, carry, and low beta. For equities we use a global market index, European market index, value, momentum, carry, and low beta.

In our framework, the funding ratio F_t, the risk aversion parameter γ, and the duration of liabilities over the duration of the set of bonds ψ are all pension fund specific. We have data on the funding ratios of pension funds. We cannot observe the risk aversion parameter directly, but we conjecture that this will be inversely related to the, so-called 'required funding ratio'. Pension funds that have a large mismatch between assets and liabilities are willing to accept more risk and to have a higher required funding ratio.[7] We also do not

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

[7]This required funding ratio is prescribed by law and is comparable to banks and insurance companies that take more risk also have a higher capital requirement (Broeders et al. 2020).

have data on the liability durations, but we have data on the fraction of active participants relative to total participants in which total participants are the active participants and the retirees combined.[8] A high ratio of active participants means a long liability duration, i.e. a high ψ.

1. **Liability structure**

   Because pension funds discount benefits by using the term structure of market interest rates (as of 2007), we predict an average exposure to the investment-grade fixed income market factor larger than one as $\psi > 1$. Because long-short factor returns have low correlations with the liability return (see Section III), we predict zero or a positive demand for the other factors.

2. **Pension fund characteristics**

   - *Funding ratio*

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

   - *Risk aversion*

     We predict that pension funds with a low risk aversion have larger exposures to factors other than the investment-grade fixed income market factor, and vice versa. Risk aversion is approximated through the inverse of the required funding ratios.

   - *Liability duration*

     We predict that pension funds with a long liability duration have a high exposure to the investment-grade fixed income market factor, but lower overall exposure to other factors, and vice versa. Liability duration is approximated through the fraction of active participants to total participants.

[8] Pension funds report liability durations as of 2007. The correlation between our measure of the liability duration and the reported liability duration equals 0.83.

III. Data

A. Pension fund returns

For the core of our analysis, we use proprietary quarterly return data on Dutch occupational pension funds from 1999Q1 through 2017Q4. The prudential supervisor in the Netherlands collects these data for regulatory purposes. Pension funds report the return on investments as the time-weighted return that takes into account the buying and selling in the asset class during the quarter. As of 2010, pension funds use standardized principles to compute returns in accordance with the Global Investment Performance Standards (GIPS). Pension funds separately report the overall portfolio return as well as the returns from the equity and the fixed income portfolios. Total returns are in euros net of transaction costs. The returns of the equity and fixed income portfolios exclude the returns from derivative positions. The sample contains 433 distinct pension funds. We correct for pension funds that report the same returns during consecutive periods. Because these are clear reporting errors, we replace the unvaried returns with missing values. To reduce estimation noise, we then exclude pension funds that report returns for less than 24 quarters in a row from the sample.

We distinguish between three different types of pension funds: corporate pension funds, industry-wide pension funds, and professional-group pension funds. Corporate pension funds execute a pension scheme for a particular company. Industry-wide pension funds organize pensions for a specific industry or sector, for example, for civil servants or for the care and welfare sector. These pension funds are typically mandatory, so the collective labor agreement in this sector prescribes that employers must join this pension fund. Professional-group pension funds provide pensions for a specific profession, such as veterinarians or pharmacists. Although corporate and professional-group pension funds are not mandatory, for historical reasons most employers offer a pension scheme to their employees. The fraction of the labor force that participates in a pension scheme exceeds 90 percent. The number of corporate pension funds in the sample is 344, the total number of industry-wide pension funds equals 79, and the number of professional-group pension funds is 10.

Table 1 shows a time series of total AUM for all pension funds that report. The AUM grew by a factor of 2.6 over the sample period. The AUM increases each year with the exceptions of a significant drop during the downturn in the stock market following the burst of the Dot-com bubble in 2002 and following the 2008 financial crisis. A continuous and significant drop in the total number of pension funds occurs during the sample period. In 2000, the total number of pension funds was 676 and reduced to a total of 200 in 2017. This drop is in particular due to a large decrease in the number of small corporate pension funds. For cost-efficiency reasons, small pension funds may decide to discontinue their operations and transfer assets and liabilities to an industry-wide pension fund or an insurance company. The table also shows the AUM of pension funds with at least 24 quarters of data in our sample. These pension funds represent on average up to 90-95 percent of the AUM of all pension funds that report per year. This large representation shows we only exclude small pension funds.

[Place Table 1 about here]

Panel A of Table 2 presents the summary statistics for pension funds' equity and fixed income returns and allocations. We measure excess returns against the 3-month Euribor rate that we get from the website of the Dutch Central Bank and use it as a proxy for the risk-free rate. The equally weighted average excess return on equities across pension funds and time equals 4.38 percent per year with a standard deviation of 19.30 percent.[9] The negative skewness indicates the equity return series has relatively strong negative values. The mean excess return on fixed income is 3.87 percent per year with a standard deviation of 7.98 percent. The high excess return on fixed income illustrates the significant drop in market interest rates over the sample period. The high kurtosis demonstrates fat tails

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

and that is, as we show later, due to the large cross-sectional variation in interest rate hedges. In our analysis, we use equally weighted returns. However, the fact that the Dutch occupational pension fund sector has a few very large industry-wide pension funds is well known. Therefore, for comparison reasons, Table 2 also presents the value-weighted statistics for returns. The value-weighted mean excess return for equities equals 4.79 and for fixed income it equals 3.71 percent.

Table 2 also presents the strategic allocations to equity and fixed income, the duration of the fixed income portfolio, the funding ratio, the required funding ratio, and the fraction of active participants relative to total participants. Pension funds invest on average 31 percent in equities and 59 percent in fixed income. The average duration of the fixed income portfolio equals 8.2 years with a substantial standard deviation of 8.7 years that indicates the pension funds vary in the extent to which they hedge interest rate risk with bonds. The funding ratio on average equals 116 percent, and the required funding ratio equals 115 percent. The fraction of active participants equals 64.25 percent on average that indicates about a third of the participants had entered the retirement phase.

[**Place Table 2 about here**]

B. Factor returns

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

For the long-short factors we use the four factors that studies have shown to perform robustly across several asset classes and markets: value, momentum, carry, and low beta.

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

1. Equity factors

We use the excess market return, value return, momentum return, carry return, and low beta return as factors that explain the pension funds' equity returns. Dutch pension funds have European as well as global equity holdings. The fraction of the equity portfolio they on average allocate to the euro area is 23 percent over the 2007-2017 period, and although we do not have data on the exposure to the euro area prior to 2007, we expect this fraction to be higher.[11] For instance, Berk and van Binsbergen (2015) show that the fraction of mutual funds that invest internationally has significantly increased over the last decade. We therefore include both global and European indices to define the market returns and to account for the currency bias (Maggiori et al. 2019). For the global market factor, we use the quarterly MSCI World Total Return Index in euros; for the European market factor, we use the Euro Stoxx 50 Total Return Index from Bloomberg in euros.[12]

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

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

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

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

The value, momentum, carry, and low beta returns are all monthly. To match with the pension funds' return cycle, we convert the monthly returns to quarterly returns by means of compounding. We assume pension funds fully hedge currency exposures and convert all dollar returns into euros.[13] The factor returns in euros are the dollar factor returns times the gross return on the exchange rate (Koijen et al. 2018) in which the exchange rate measures the number of euros per dollar. For the summary statistics, we furthermore convert quarterly returns into annual ones.

Panel B of Table 2 contains the summary statistics for the factor returns. Within equities, the low beta factor has the highest annualized return (11.03 percent), while value has the lowest (4.00 percent). Next to the market factors, momentum is the most volatile long-short factor over the sample period. Table 3 presents the correlation matrix of factor returns. The strikingly high negative correlation between value and momentum is a well-known stylized fact in the literature and is documented in Asness et al. (2013).

2. Fixed income factors

Compared to equities, Dutch pension funds invest significantly less globally within their fixed income portfolios. Measured over the period from 2007 through 2017, they invested

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

on average 87 percent of the fixed income portfolio in the euro area.[14] Again, we expect this fraction to be even larger prior to 2007. A currency bias for euro fixed income is logical because pension funds' liabilities are also denominated in euros, and fixed income is mainly used to hedge liabilities. We therefore use European factors for fixed income, as opposed to global factors for equities. Because bond returns are largely explained by duration and credit risk, we use the Bloomberg Barclays Euro Aggregate Bond Index and the Bloomberg Barclays Euro High Yield Index in euros as the market and credit factors respectively.[15] Table 2 shows that both the equally and value-weighted excess fixed income returns of pension funds are above the excess return of the investment-grade fixed income index. Pension funds have an incentive to invest in bonds with a high duration to match the high duration of their liabilities. The average duration of the fixed income portfolio equals 8.2 (Table 2). As such, benchmark durations are typically lower than the portfolio duration of pension funds. An upward-sloping term structure of interest rates therefore (in part) explains the higher pension fund returns.

As opposed to global, European fixed income long-short factors are not available, so we construct the value, momentum, carry, and low beta factors following the methods of Asness et al. (2013), Koijen et al. (2018), and Frazzini and Pedersen (2014). As the purpose of this paper is to gain an insight into the factor exposures of institutional investors rather than the construction of factor returns themselves, we use the exact definitions of the aforementioned authors. We include the following European countries in constructing our factors: Austria, Belgium, Denmark, Finland, France, Germany, Italy, Netherlands, Norway, Spain, Sweden, Switzerland, and the UK. All these countries have investment-grade ratings over our sample

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

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

The Bloomberg Barclays Euro High Yield Index measures the market for non-investment grade, fixed-rate corporate bonds denominated in euros. Inclusion is based on the currency of issue and not the domicile of the issuer. The index excludes emerging market debt.

period. Appendix B describes the exact procedure for how we construct the factors. For all three factors, we assume the investor fully hedges currency exposures against the euro. Again, we convert monthly returns to quarterly returns by means of compounding. In the case of fixed income, carry has the highest annualized return (1.84 percent) followed by momentum (1.24 percent) and value (1.17). Low beta has a relative low average return equal to 0.86 percent, which is consistent with the findings in Frazzini and Pedersen (2014) who do not find a significant average return for the global low beta bond factor. Value has the highest standard deviation (5.56 percent) followed by momentum (4.54), carry (4.52), and low beta (4.41). Figure 1 shows the evolution of long-short fixed income factors over time. Table 3 also confirms the substantial negative correlation between value and momentum for fixed income (Asness et al. 2013).

[Place Table 3 about here]

[Place Figure 1 about here]

IV. Unconditional factor exposures

In this section, we proceed with the estimation of the unconditional factor exposures. We take three sequential approaches to account for measurement errors in the factor exposures, where measurement error stems from the infrequent observations of pension fund returns. First, we run time-series OLS regressions. Second, we use a random-coefficient model to estimate priors on factor exposures. Third, we derive posterior factor exposures. In Subsection D we show the implications of heterogeneity in factor exposures for heterogeneity in expected performance across pension funds. Subsection E performs a variance decomposition to quantify how much of the cross-sectional differences in average returns are explained by the factors.

A. OLS factor exposures

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 excess factor exposures by regressing the excess returns of pension fund $i = 1, ..., N$ for asset class a on the excess factor returns in the following way:

$$r_{it}^{a} - r_{ft} = \alpha_i^a + \beta_i^{a'} f_t^a + \epsilon_{it}^a, \quad \text{for} \quad i = 1, ..., N, \tag{14}$$

in which r_{ft} is our proxy for the risk-free rate, f_t^a is a vector of factor returns of length K for asset class a, and ϵ_{it}^a is the idiosyncratic error term with standard deviation σ_i^a. For equities, vector f_t^E contains the following six elements: the global excess market return, the European excess market return, the global value stock return, the global momentum stock return, the global carry stock return, and the global low beta stock return. For fixed income, the vector f_t^{FI} has the following six elements: the European excess investment-grade fixed income market return, the European excess high yield fixed income return, the European value fixed income return, the European momentum fixed income return, the European carry fixed income return, and the European low beta fixed income return. In the remainder of the paper we drop the superscript a to simplify the notations. In Table 4, we present the cross-sectional mean and standard deviation of the estimated betas using the time-series OLS in Equation (14).

[Place Table 4 about here]

B. Prior factor exposures

The estimated factor exposures using the time-series OLS in Equation (14) suffer from measurement error because we only observe quarterly returns (Merton 1980). The cross-sectional mean and standard deviation from the times-series estimates shown in Table 4 may therefore substantially deviate from the true moments. Because the focus is on the cross-sectional mean and standard deviation of factor exposures, we correct for this deviation by using a prior on the mean and the variance in the factor exposures that we derive from a random-coefficients model. Compared to a standard regression model in which the parameters are fixed to a single value, the random-coefficients model allows for cross-sectional variation in the parameters. We specify the random-coefficients model as follows:

$$\begin{aligned} r_{it} - r_{ft} &= \alpha_i + \beta_i' f_t + \epsilon_{it} \\ &= \alpha + \beta' f_t + v_i' f_t + u_i + \epsilon_{it}, \end{aligned} \tag{15}$$

in which v_i is a vector of length L that captures all the random-effect coefficients, and ϵ_{it} is the idiosyncratic error term with variance σ_i. Furthermore, we assume that the length of vector L is equal to the number of asset classes K; in other words, we allow all factor exposures to vary across pension funds. The exact procedure for estimating the random-coefficients model is in the Internet Appendix B.

We use the distribution of the regression coefficients across pension funds as the prior distribution in the analysis. Following Vasicek (1973), Elton et al. (2003), and Cosemans et al. (2016), we then adjust the estimated factor exposures from Equation (14) to the prior to obtain posterior betas. The prior betas are now defined as:

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

in which $\hat{\beta}^k$ is the fixed-effect estimator, and $\hat{\sigma}^2_{\beta^k}$ is the variance of the random effect from Equation (15). Table 5 shows the results of the random-coefficient model. The table shows both the estimates and the corresponding standard errors. The standard errors allow us to test the existence of true heterogeneity in the factor exposures. We find significant average factor exposures in both the equity and the fixed income portfolios. Similarly, we also find significant cross-sectional heterogeneity in all factor exposures, except for momentum in the fixed income portfolios. A detailed interpretation of the coefficient estimates appears in the Internet Appendix B.

[Place Table 5 about here]

C. Posterior factor exposures

Now that we have the prior, we can derive the posterior factor exposures in this subsection. We follow the formal procedure of Vasicek (1973) that combines the sample estimate of the factor exposures with the prior to obtain the posterior factor exposures. These exposures are approximately normally distributed with the following mean and variance:

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

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

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

For equities, Table 6 shows the average exposures to the world and European market factors as equaling 0.67 and 0.28 respectively and with standard deviations equaling 0.15 and 0.13. The sum of market exposures equals 0.95 that indicates the pension funds, on average, take slightly less systemic risk than the market portfolio. The standard deviations of the posterior market exposures shrink by about one-third compared to the time-series regressions in Table 4, which indicates that the substantial variation in the market exposures remains after correcting for the measurement error. The average exposures to value, momentum, carry, and low beta equal -0.05, -0.04, -0.04, and 0.08, respectively. The standard deviation in factor exposures for value, momentum, carry and low beta are 0.05, 0.03, 0.10, and 0.07, respectively. The standard deviation in the posterior factor exposures shrinks by two-thirds for value, three-fourths for momentum, two-thirds for carry, and one-half for low beta compared to the times-series regressions in Table 4. A substantial part of the cross-sectional variation in the factor exposures detected in Table 4 is thus the result of measurement error. Yet, the heterogeneity in factor exposures remains, especially for value, carry, and low beta.

For fixed income, the average exposure to the investment-grade market factor equals 1.16, and the standard deviation equals 0.27. The standard deviation of the posterior market exposure shrinks by one-fourth compared to the time-series regressions in Table 4, which indicates substantial variation in market exposures remains after correcting for the measurement error. The average exposures to credit risk, value, momentum, carry, and low beta are 0.02, -0.17, 0.06, -0.07, and 0.22, respectively. The cross-sectional standard deviations of value, carry, and low beta equal 0.10 and 0.04, and 0.15 respectively. Again, substantial variation in factor exposures from the time-series regressions is due to measurement error, although the heterogeneity in the factor exposures remains, especially for value and low beta. Because we are not able to detect any variation in the exposure to momentum, 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 6 about here**]

D. *Heterogeneity in expected returns*

Variation in factor exposures has consequences for the expected returns and thus on the expected performance differences across pension funds. To determine these differences, we compute for each pension fund the contribution of the market and the long-short factor exposures to the expected returns. In this subsection, we use the posterior betas obtained from Equation (17). The contribution from the market exposure to the expected return is computed as:

$$\mathbb{E}(r_i^M) = \tilde{\beta}_i^{M\prime} \lambda^M \quad \text{for} \quad i = 1, ..., N, \tag{19}$$

in which for equities $\tilde{\beta}_i^M = [\tilde{\beta}_i^{M,W}; \tilde{\beta}_i^{M,EU}]$ and $\lambda^M = [\lambda^{M,W}; \lambda^{M,EU}]$ and for fixed income $\tilde{\beta}_i^M = [\tilde{\beta}_i^{M,EU}; \tilde{\beta}_i^{HY,EU}]$ and $\lambda^M = [\lambda^{M,EU}; \lambda^{HY,EU}]$. We estimate λ's as the historical average returns. We compute the contribution of the long-short factor exposures to the expected returns similarly:

$$\mathbb{E}(r_i^F) = \mathbb{E}(r_i - r_i^M) = \sum_{k=3}^{K} \tilde{\beta}_i^k \lambda^k \quad \text{for} \quad i = 1, ..., N. \tag{20}$$

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

The empirical distributions of Equations (19) and (20) deliver the variation in the expected returns due to differences in the factor exposures. For equities, Table 7 shows that taking both market and long-short factors together, the overall contribution of the factor exposures varies between 2.27 and 6.53 percentage points. Pension funds with the highest market exposure have an expected return on the market that is equal to 4.70 percentage points, while the expected return for pension funds with the lowest market exposure equals 4.05 percentage points. For the long-short factors, the dispersion is much larger for carry and low beta compared to the market. The expected return contribution of the carry factors equals 0.36 percentage points at the highest and −1.11 percentage points at the lowest percentile. For low beta it varies between 1.76 and −0.08.

For fixed income, taking both market and long-short factors together, the overall contributions of the factor exposures vary between 1.92 and 3.89 percentage points. The variation in the contributions of market exposures are larger than for equities and vary between 2.07 and 4.04 percentage points. The long-short factors play a subordinate role. The negative contribution of the factor exposures is due to the typically negative exposure to value and carry factors.

Panel C of Table 7 shows the overall contribution of the factors to pension funds' portfolios. The overall exposure is computed as the sum of the equity exposure times the equity weight and the fixed income exposure times the fixed income weight. All factors taken together, the contribution to the expected returns differs 2.26 percentage points. In other words, pension funds with the highest factor exposures versus pension funds with the lowest factor exposures have a 2.26 percentage point higher expected return on the entire portfolio. The contribution of the market factor has values that vary between 2.84 and 4.05 percentage points for the entire portfolio and the contribution of long-short factor exposures has values that vary between −0.41 and 0.65 percentage points.

[Place Table 7 about here]

Figure 2 plots the realized cumulative returns of pension funds that are in our sample over the entire period for the 10th percentile and the 90th percentile (taking all factors together). For equities, the realized cumulative return equals 93 percentage points for the 90th percentile and 74 percentage points for the 10th percentile. This is equivalent to a difference in realized annual returns of 1 percentage points. The cumulative returns of the pension funds in the 90th percentile indeed coincide with the pattern of the low beta return (Figure 1): they performed worse than pension funds with no exposure to low beta during the early part of our sample and during the global financial crisis, but outperformed during the second part of our sample.

For fixed income, the realized cumulative return equals 134 percent for the 90th percentile and 80 percent for the 10th percentile. This is equivalent to a difference in realized annual returns of 2.84 percentage points. The cumulative return of pension funds in the 90th percentile sharply increased during the second half of the sample as a result of the high exposure to the fixed income market index and the simultaneous decline in interest rates. In the next section, we show that part of the heterogeneity in returns is driven by differences in the liability hedge demand.

[Place Figure 2 about here]

E. Variance decomposition

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

$$\tilde{\mu}_i = \tilde{\alpha}_i + \tilde{\beta}_i' \lambda_i \quad \text{for} \quad i = 1, ..., N, \tag{21}$$

in which λ_i is the average factor return over the period in which pension fund i is in the sample. Second, we take the cross-sectional covariance of each side with $\tilde{\mu}$, the vector of average 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:

$$1 = \frac{\mathrm{Cov}(\tilde{\beta}' \lambda, \tilde{\mu}) + \mathrm{Cov}(\tilde{\alpha}, \tilde{\mu})}{\mathrm{Var}(\tilde{\mu})} = \frac{\sum_{k=1}^{K} \mathrm{Cov}(\tilde{\beta}^{k\prime} \lambda^k, \tilde{\mu}) + \mathrm{Cov}(\tilde{\alpha}, \tilde{\mu})}{\mathrm{Var}(\tilde{\mu})}, \tag{22}$$

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

Table 8 shows the results for both equity and fixed income returns. The exposures to the excess global and European market returns for equity explain 68.87 and 15.13 percent of the variation in average equity returns, respectively. For the long-short factors, the one with the most explanatory power is low beta, and it explains 8.14 percent of the variation in average returns. Value explains 5.46, carry 5.74, and momentum 0.69 percent of the variation in average returns. The total exposure to long-short factors thus explains 20.03 percent of the average returns. Alpha has negligible explanatory power for average returns. This is consistent with the highest heterogeneity found for global and European market factors, followed by the long-short factors.[16]

For fixed income, the European excess investment-grade market return explains 91.77 percent of the variation in average returns and the high yield return 5.43 percent. Low beta, value, and carry explain 11.20, −10.07, and −4.54 of the variation in average returns. The negative signs indicate that the pension funds with positive exposure to value and carry have lower average returns: pension funds with the highest expected returns have the highest exposures to the market index and at the same time the lowest exposures to value and carry (Table 7). Thus, similar to equities, we find that long-short factors explain approximately 28.35 percent in absolute value of the cross-sectional differences in the average fixed income returns.

[Place Table 8 about here]

V. What drives factor exposures?

The previous sections have shown that some factor exposures are on average negative, but substantial heterogeneity in the factor exposures across pension funds exists. In this section we aim to understand the drivers behind these factor exposures by testing the implications of our theoretical framework in Section II. We start with the liability structure, followed by pension fund characteristics that include the funding ratio, risk-aversion, liability duration,

[16] Further, the low heterogeneity in the expected returns for the market as a whole in Subsection D is due to merging the of global and European markets.

size, and asset managers. We finish the section by deriving pension funds' implied beliefs about factor returns.

A. Liability structure

Do pension fund liabilities explain negative factor exposures? Our theoretical framework predicts that hedging demand for assets depends on the correlation between liability return and the factor return. As we hypothesize, interest rate risk is the core driver of liability returns, as liabilities are valued against the nominal term-structure of market interest rates. We show here that this also holds empirically.

Next to interest rates, also indexation of benefits or benefit reductions, if any, affect liability returns. Other components such as changes in survival probability or participants that transfer their pension benefits to another pension fund also affect liability returns. To formally test the determinants of liability returns, we regress liability returns on all factors:

$$r_{it}^{L} - r_{ft} = \alpha_i + \beta_i^{'} f_t + \epsilon_{it}, \quad \text{for} \quad i = 1, ..., N, \tag{23}$$

We compute liability returns as follows: Denote L_t as the value of the liabilities at time t. During the quarter pension funds receive new contributions C_t and pay out pension benefits B_t. The net cash inflow equals $I_t = C_t - B_t$. A positive net cash inflow can be interpreted as an additional purchase of bonds. We assume that the net cash flow materializes exactly halfway through the quarter. The return on the liabilities is then given by:

$$r_{t+1}^{L} = \frac{L_{t+1} - L_t - I_t}{L_t + \frac{1}{2} I_t}. \tag{24}$$

Liability returns contain substantial noise for main two reasons. First, non-market factors such as benefit transfers between pension funds affect liability returns. Second, we have to make an assumption on the timing of cash flows during the quarter. Therefore, to reduce measurement error, we only estimate (23) for pension funds that are always in the sample from 2007Q1 to 2017Q4 (76 pension funds).[17] The results are in Table 9.

The investment-grade fixed income market factor primarily drives the liability return, with an average exposure equal to 2.29. This exposure is consistent with the liability durations of pension funds. The average liability duration of pension funds equals approximately 17 years (Broeders et al. 2020), while the average duration of a typical fixed income market index equals roughly only seven years. The exposure to all the other factors are not statistically significant, except only borderline significant for carry. Given that we estimate 12 coefficients, we expect one coefficient to be significant at the 10 percent significance level due to type II errors. Overall, these findings indeed confirm that interest rate risk is the core driver of liability returns, which explains an average exposure larger than one to the investment-grade fixed income market factor. However, the exposure of the liability return to long-short factors does not explain the average negative exposures to value and carry. These negative factor exposures have an aggregate negative contribution to expected annual returns of 0.47 percentage points.[18] This is an economically sizable effect because its equivalent to expected retirement income that is 11 percent lower over a 40-year accrual phase.

[Place Table 9 about here]

B. Pension funds' characteristics

In this subsection we analyze the effect of pension funds' characteristics on factor exposures. We estimate the impact of the funding ratio, the risk-aversion (represented by the inverse of the required funding ratio), the liability duration (represented by the ratio of active participants to total participants in which total participants equal the active participants

[17]The data on liabilities are only available over the period 2007Q1-2017Q4.

[18]The negative exposures to the equity factors contribute 27 basis points and the negative fixed income factor exposures contribute 20 basis points.

and the retirees), the AUM for the asset class, and the delegated asset managers on factor exposures. The first three characteristics follow directly from our theoretical framework in Section II, the other two are included following the literature.

We perform a panel data regression of the pension funds' returns that includes the funding ratio, the proxy for risk-aversion, the proxy for liability duration, size, and asset managers' quarter fixed effects that are interacted with the factor returns:

$$\begin{aligned} r^e_{it} &= \delta_0' f_t + \delta_1' f_t \times \mathrm{FR}_{it-1} + \delta_2' f_t \times \gamma_{it-1} + \delta_3' f_t \times \mathrm{DUR}_{it-1} + \delta_4' f_t \times \mathrm{AUM}_{it-1} \\ &+ \delta_5'(f_t \times AM'_{it-1})\iota_5 + \epsilon_{it}, \end{aligned} \tag{25}$$

in which FR_{it-1} is the funding ratio of pension fund i at time $t-1$, γ_{it-1} is the proxy of the risk-aversion of pension fund i at time $t-1$, DUR_{it-1} is the proxy of the liability duration for pension fund i at time $t-1$, AUM_{it-1} is the AUM for pension fund i at time $t-1$ for the corresponding asset class, and AM_{it-1} is a vector of length five and equals one if the corresponding asset manager is employed by pension fund i during the quarter $[t-1,t]$, and zero otherwise, and ι_5 is a vector of ones with length five. The five asset managers we analyze are most often employed by Dutch pension funds. We demean FR_{it-1}, γ_{it-1}, DUR_{it-1}, and AUM_{it-1} such that δ_0 can be interpreted as the average pension fund.

1. Funding ratio

Our theoretical framework predicts that pension funds with a low funding ratio should have a high exposure to the fixed income market factor, and vice versa. Moreover, the lower the funding ratio, the less room for the speculative portfolio if the borrowing constraint is binding. Hence, we predict that on average, lower exposures will exist to factors other than the fixed income market factor for pension funds with low funding ratios, and vice versa. For equities, we find that pension funds with a high funding ratio have only a slightly higher exposure to carry (Table 10). A one standard deviation increase in the funding ratio

(0.16) increases the carry exposure by 0.01. For fixed income, we find that pension funds with a high funding ratio have less exposure to the market factor and more exposure to the credit factor (Table 11). A one standard deviation increase in the funding ratio decreases the exposure to the market factor by 0.16 and increases the exposure to the credit factor by 0.02. Overall, these findings are consistent with our theoretical framework: pension funds with a low funding ratio invest more in investment-grade fixed income securities that correlate positively with their liabilities, while they have a lower aggregate exposure to the other factors.

Andonov et al. (2017) find the opposite result for US public pension funds. This difference is driven by regulation: The discount rate of US public pension links to expected returns on the assets, whereas Dutch pension funds have to use a discount rate that links to market interest rates. A discount rate based on market interest rates is widely used and the standard for US private pension funds, Canadian, and other European pension funds.

2. Risk aversion

We use the inverse of the required funding ratio as an implicit measure of the risk-aversion in which $\gamma \propto 1/\text{RFR}$, as described in Section II. Our theoretical framework predicts that pension funds with a higher risk-aversion coefficient should have a lower exposure to riskier assets. For equities, a one standard deviation increase in the proxy for risk-aversion (0.04) slightly decreases the exposure to the global market factor by 0.02. The overall exposure to factors for equities is thus slightly larger for pension funds with lower implicit risk-aversion. For fixed income, a higher inverse of the required funding ratio increases the exposure to the market factor substantially and the exposure to momentum slightly. A one standard deviation increase in the implicit risk-aversion coefficient increases the exposure to the market factor by 0.40 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. A one standard deviation increase 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 0.16, and low beta by 0.08. 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.

3. Liability duration

The fraction of active participants (non-retirees) is a measure for the liability duration. A high fraction of active participants relative to retirees means a high liability duration, and vice versa. Table 2 shows that the average fraction of active participants equals 64 percent over our sample period and has a standard deviation of 25 percent. Our theoretical framework predicts that pension funds with a high liability duration should have a higher exposure to the fixed income market factor, and vice versa. Moreover, when the liability duration is higher, there is less room for the speculative portfolio. Therefore, we predict that if the borrow constraint is binding, there will be lower exposures to factors other than the fixed income market factor for pension funds with high liability durations, and vice versa. The liability duration is not related to the equity factors. For fixed income, pension funds with a low liability duration have less exposure to the market factor and more exposure to the credit factor. A one standard deviation decrease in our proxy for the liability duration (0.25) decreases the exposure to the market factor by 0.37 and increases the exposure to credit by 0.03. Pension funds with a low liability duration also have higher exposure to carry and low beta. A one standard deviation decrease in the liability duration increases the exposure to carry and low beta by 0.18 and 0.10. Again, these findings are consistent with our theoretical framework.

4. Size

Size might affect market and long-short factor exposures for two competing reasons. First, large pension funds generally have economies of scale and therefore can bring more expertise to their investment process. As a result we might expect large funds to invest in a more globally and sophisticated manner. Second, due to the price effect of large trades – see, for example, Easley and O'Hara (1987) – pension funds with a substantial AUM in a specific asset class are constrained and might choose to implement factor investing on a low scale relative to pension funds with a lower AUM. Table 10 shows the results for equities. Size has a positive and significant effect on the exposure to the excess global market return, and a negative and significant effect on the exposure to the excess European market return. A pension fund that is 10 times larger has a 0.04 higher exposure to the global market and a 0.04 lower exposure to the European market. This finding confirms earlier conjectures that large pension funds have the means to diversify their equity investments more globally than small pension funds. For equities, size has no effect on the long-short factor exposures except for a slightly positive effect for low beta. In Table 11, size has a positive effect on the exposure to the credit factor for fixed income. A pension fund that is 10 times larger in terms of AUM has an exposure to the credit factor that is 0.02 larger. Size has no effect on the exposure to the long-short factors. These results thus do not confirm the conjecture that large pension funds might be constrained in implementing factor investing.

5. Asset managers

Pension funds do not necessarily manage assets themselves. In fact, most Dutch pension funds use external, for-profit asset managers to implement their investment strategy through asset-management mandates. Although information on these mandates is scarce, pension funds do report the name of the asset-management companies that execute at least 30 percent of the total AUM on behalf of the pension fund.[19] These names are available for the period from 2009 through 2016 which allows us to analyze the effect the asset managers have on factor exposures. Differences in factor exposures can arise in multiple ways. First, the pension fund might communicate the factor strategies they wish to delegate

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

to the asset manager. Second, the asset manager might select particular assets within the asset-management mandate that correlate with long-short factors. Third, a combination of strategies communicated by the board of the pension fund and the asset manager's own strategy might result in factor exposures that amplify or weaken each other. Unfortunately, we do not have information on the asset-management mandates between the pension fund and the delegated asset managers, and therefore we cannot isolate those effects. The results cannot be reduced to mindful decision-making by either the pension fund or the asset manager. In total, we distinguish 56 different asset managers. We analyze the effect of the five asset managers that are most often employed by Dutch pension funds. In total, these asset managers manage at least 30 percent or 123 pension funds in our sample of 350 pension funds over the period from 2009 to 2016.

For equities, Table 10 shows that the exposure to the market interacted with the fixed effects of the asset managers and shows that the pension funds with asset managers 2, 4, and 5 have a significantly higher exposure to the excess global market return. The pension funds with asset manager 2 have a lower exposure to the excess European market return. The interaction of the fixed effects of asset managers with the long-short factor exposures shows that the asset managers employed by the pension funds affect the eventual factor exposures. The pension funds with asset managers 1, 2, 4, and 5 have lower exposures to value of -0.05, -0.05, -0.04, and -0.10, respectively. On the other hand, the pension funds with asset manager 3 have a statistically and significantly higher exposure to value: 0.24 compared to the average exposure of 0.04. For momentum, the pension funds with asset manager 5 have a more negative exposure to momentum than average. The pension funds with asset manager 3 have a higher exposure to momentum, 0.04, compared to the average momentum exposure, -0.04. For carry, the pension funds with asset managers 3 and 5 have a higher exposure to carry: 0.11 and 0.09 compared to 0.03. For low beta, the pension funds with asset manager 2 have a lower exposure to low beta: 0.03 relative to the average of 0.06.

In Table 11, we find that pension funds that employ asset managers 3, 4, or 5 have a higher exposure to the market. For the credit factor, the pension funds that delegate their assets to asset managers 4 and 5 have lower exposures, while the exposure is higher for asset manager 1. For value, asset managers 2, 3, and 4 have a less negative exposure to value: equal to -0.09, -0.09, and -0.13 respectively. Asset manager 4 has a higher exposure to momentum of 0.06. For carry, asset managers 1, 3, and 4 lead to substantially lower carry exposures. Asset managers 2 and 5 have lower exposures to the low beta factor of -0.11 and -0.25 respectively.

Why do asset managers have such significant effects on factor exposures? Asset managers may have different beliefs about factors. As shown in Binsbergen et al. (2008), the optimal solution to the mean-variance optimization problem for a pension plan is generally different from the optimal combination of the mean-variance efficient portfolios of the asset managers employed by the pension plan. Blake et al. (2013) explain the move of pension funds toward decentralization as exploiting the increased skill of specialized managers as well as benefiting from the competition among the asset managers.

[Place Table 10 about here]

[Place Table 11 about here]

C. Disentangling heterogeneity in performance in the speculative and liability hedge portfolio

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

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

$$\tilde{\beta}^k_{adj,i} = \tilde{\beta}^k_i - \hat{\delta}^k_1 \times \overline{\mathrm{FR}}_i - \hat{\delta}^k_2 \times \overline{\gamma_i} - \hat{\delta}^k_3 \times \overline{\mathrm{DUR}}_i \quad \text{for} \quad k = 1, ..., K \quad \text{and} \quad i = 1, ..., N. \tag{26}$$

Because the time series averages $\overline{\mathrm{FR}}$, $\overline{\gamma}$, and $\overline{\mathrm{DUR}}$ are defined relative to the cross-sectional sample average, the adjusted factor exposures increase when the funding ratio is higher than average, the risk-aversion is lower than average, or the liability duration is lower than average, and vice versa.

We redo the analysis in Section IV (subsection D) and the results are summarized in Table 12. Pension funds with the highest factor exposures versus pension funds with the lowest factor exposures have a 1.04 percentage point higher expected return on the entire portfolio. The contribution of the market factor has values that vary between 3.11 and 3.75 percent for the entire portfolio and the contribution of long-short factor exposures has values that vary between −0.04 and 0.36 percent. A total return difference of 1.04 percentage points that cannot be explained by the liability hedge demand is an economically sizable effect. A 1.04 percentage points lower annual return decreases expected retirement income by 24 percent over a 40-year accrual phase or increases contributions by 31 percent to get the same income.

D. Implied beliefs on expected factor returns

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

$$\mu_i \approx \gamma_i \delta_i \Sigma_i (w_i - q_i) - \lambda \mathbf{1} \qquad \text{for} \qquad i = 1, ..., N, \tag{27}$$

where 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 is the portfolio weights, q_i is 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 short-sale constraint. The total precision parameter measures the informedness of the fund manager about future returns and is the sum of two parts $\delta_i = \tau^{-1} + \tau_i^{-1}$: τ^{-1} is the precision of the prior on expected returns, and τ_i^{-1} is the precision of a signal about expected returns of fund manager i.

The true beliefs are an affine function of 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:

$$\hat{\mu}_i = \Sigma_i (w_i - q_i) \qquad \text{for} \qquad i = 1, ..., N. \tag{28}$$

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

We refrain from private signals and set $\tau_i = 0$. 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 ($\tau_i = 0$), 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:

$$p(\mu_0) \sim N(\mu, \Sigma). \tag{29}$$

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

Using our model in Section II in an unconditional setting and applying the above assumptions to (27), we can derive the implied beliefs about the expected factor returns for pension fund i as:

$$\hat{\mathbb{E}}_i[r_{t+1}] = \gamma_i \text{Var}[r_{t+1}](\beta_i - q_i) - \gamma_i \text{Cov}(r^b_{t+1}\iota_N, r_{t+1})\psi_i \iota_N F_i^{-1} \qquad \text{for} \qquad i = 1, ..., N. \tag{30}$$

From Subsection A, we know that $\text{Cov}(r^b_{t+1}\iota_N, r_{t+1})$ is only nonzero for the investment-grade fixed income market factor. Therefore, the hedging component only matters for deriving the implied beliefs about the investment-grade fixed income factor. Also, as opposed to Shumway et al. (2011), we do not get rid of γ_i when estimating the implied beliefs as we do have information about the risk-aversion coefficient of pension funds.

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 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 an risk-aversion parameter of five for the average pension fund. We estimate ψ_i by $\psi_i \approx 3 \times$ ratio actives in which ratio actives is the fraction of active participants. The average fraction of active participants equals 64 percent in which $\psi_i = 3 \times 0.64 = 2$ for the average pension fund, as found in Subsection A.

Table 13 shows the results for the annualized implied beliefs (Equation 30) on the expected factor returns and conditional on all pension funds having the same informedness. For equities, a median pension fund has positive implied beliefs about the European market factor (1.37 percent), while they are slightly negative for the global market factor (-0.29 percent). 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 0.52 percent and equals -0.49 percent for momentum, -0.25 for carry, and 0.53 for low beta. This belief means that pension funds on average expect 1 percentage point higher returns on value and low beta compared to momentum. There is substantial heterogeneity in the implied beliefs about the expected factor returns, especially for value, momentum, and low beta. For instance, for value the pension funds with the most pessimistic views on value expect a negative return of 0.44 percent on top of the benchmark return, while for pension funds with the most optimistic views this return equals a positive 1.39 percent.

For fixed income, the median implied beliefs on the investment-grade market factor equals -0.07 percent. The heterogeneity in the implied beliefs for the market factor is limited and indicates that when correcting for the hedging demand, pension funds have similar beliefs about the market factor. For the credit factor, the implied beliefs equal on average -0.33 and have substantial heterogeneity across pension funds. They range from -1.19 to 0.56 percent. For the value factor, the implied beliefs equal -0.48, 0.29 for momentum, -0.28 for carry, and 0.49 for low beta. The greatest heterogeneity in the implied beliefs on the expected returns exists for low beta in which pension funds with the most pessimistic views on low beta expect a negative return of 0.09 percent, while pension funds with the most optimistic views expect a positive return of 0.81 percent, both are on top of the benchmark return.

[Place Table 13 about here]

VI. Conditional factor exposures

In the previous sections we analyzed the unconditional factor exposures. Yet, if pension funds change their investment strategies over time, factor exposures may change substantially over time as well. Therefore, in this section we estimate the conditional factor exposures and we seek to explain the drivers behind these changes in factor exposures. We take the following three approaches: First, we estimate rolling factor exposures. Second, we analyze how factor exposures respond to external events that we conjecture to be relevant for pension fund investing. Third, we show that changes in factor exposures are due to active changes in country allocations.

A. *Rolling factor exposures*

We estimate the rolling factor exposures by using overlapping window regressions. We use an estimation window of 20 quarters to estimate the factor exposures for each pension fund $i = 1, ..., N_t$ in the corresponding window $[t - w + 1, t]$, $t = w, ..., T$, with $w = 20$.

Figure 3 shows the cross-sectional average of rolling beta estimates for all factor exposures within equity and fixed income portfolios. Panel A shows the results for the market factors and the credit factor for fixed income. Panel B shows the results for the long-short factors.

The figure has some striking patterns. We observe that the time variation in the conditional factor exposures for equities is only minor. The factor exposures for fixed income are far more extreme than for equities and also vary much more over time. In most cases, the average factor exposure is at least three times as large for fixed income compared to that for equities. The average factor exposures can get as low as -0.8 (for the value factor exposure in 2012) and as high as 0.9 (for the carry and momentum factor exposures in 2011).

We perform a return decomposition in Internet Appendix C that shows the contribution of the conditional factor exposures to the average realized returns. For equities, we observe that the market factor exposures explain most of the realized returns over time. The contribution of the long-short factors is low. By contrast, the long-short factors do matter for realized fixed income returns over time, particularly during the 2010-2015 period. For instance, during the period of 2012-2014, the negative exposure to value has often contributed negatively to the average returns.

[Place Figure 3 about here]

B. Events

We consider four events that might affect pension funds' factor exposures: (1) the introduction of risk-based pension fund regulation on January 1, 2007, (2) the start of the Great Financial Crisis (GFC) with the collapse of the investment bank Lehman Brothers on September 15, 2008, (3) the announcement of the government of Cyprus that it would seek a bailout from the European Union and the International Monetary Fund on June 25, 2012, and (4) a change in pension fund regulation on January 1, 2015. As the collapse of Lehman Brothers and the euro sovereign debt crisis are well known, we only explain the changes in regulation in more detail.

The regulator in the Netherlands introduced risk-based regulation for pension funds as of the start of 2007. The core of these regulations is similar to Solvency II for European insurance companies in which capital requirements are aligned with the risks of an insurance company.[20] Key elements of the Dutch pension regulations include marked-to-market valuation of both assets and liabilities, funding requirements, and recovery plans. The marked-to-market valuation of defined benefit liabilities means that pension funds discount liabilities against a zero coupon term structure of market interest rates. There are two funding requirements. The minimum funding requirement is a flat rate equal to a funding

[20]US defined benefit pension funds face less strict funding requirements compared to Dutch pension funds. By contrast, in the US the Pension Benefit Guaranty Corporation (PBGC) insures benefits for private pension participants, and state and local governments insure benefits for public pension plan participants. The Netherlands does not have such pension insurance schemes in place.

ratio of about 104.2 percent.[21] In contrast, the required funding rate is based on a pension fund's risk profile and is calculated such that the probability that the funding ratio falls below 100 percent on a one-year horizon equals 2.5 percent. For a median pension fund this ratio amounts to a required funding ratio of 116 percent.

In case a pension fund is not compliant with funding requirements, it files a recovery plan to the supervisor. Recovery measures may include an increase in contributions, a reduction of the future benefit accrual rate or, as a measure of last resort, a reduction in accrued benefits. The regulation of 2007 contained an initial 15-year recovery period to meet the required funding rate and an initial 3-year recovery period to meet the minimum funding requirement. As of 2015, the regulator changed this regulation. Under the new regulation, recovery periods are a maximum of 10 years and are independent of the funding requirement. This timeframe allows pension funds to better smooth the impact of negative shocks over time. The change in these dynamics has had effects on pension fund investment and risk management.[22]

Figure 3 displays vertical lines that indicate the four events. The equity factor exposures only change slightly after the events. We observe a minor drop in the average exposure to the global market factor and a slight increase in the European market factor after the start of the GFC. At the same time, we also observe a minor drop in the exposure to momentum and a temporary drop in the exposure to carry. During the sovereign debt crisis as well as after the change in regulation in 2015, we observe a decrease in the exposure to low beta. Over the entire period, there is an increase in the exposure to the global market factor, and a decrease in the exposure to the European market factor visible.

For fixed income, the factor exposures change much more rapidly after the events. After the introduction of risk-based regulation in 2007, we see, for example, an increase in the average exposure to the market as pension funds started to hedge interest rate risk by

[21] www.toezicht.dnb.nl/2/50-202138.jsp

[22] The change reduced the incentive to hedge the mismatch between the interest rate risk of the asset and the liabilities. This policy paper was produced by De Nederlandsche Bank on behalf of the government: www.eerstekamer.nl/overig/20151217/wijziging_risicoprofiel/f=y.pdf to explains this change.

investing more in bonds with long durations (or using interest rate swaps, but this part we do not observe in our data), consistent with the predictions of our model. The exposure to the market really took off around the euro sovereign debt crisis. Over the period 2003 to 2015, exposure to the market factor increased from 1 to approximately 1.4. This finding is consistent with the hunt for duration behavior as shown in Domanski et al. (2017) for German insurance companies during periods of low interest rates. However, the exposure to the market dropped temporarily after the change in Dutch pension regulation, as pension funds' incentives to hedge interest rate risk dropped. At the same time, there was a substantial increase in the credit risk factor (from approximately 0 to 0.3).

The momentum, carry, and low beta factor exposures increased sharply following the start of the GFC in 2008 and then reversed sharply around the peak of the euro sovereign debt crisis. For value, this reversal had already happened in 2010. The euro sovereign debt crisis moved Dutch pension funds away from government bonds in southern Europe to safe haven bonds with lower carry ranks, such as German and Dutch government bonds, which affected factor exposures dramatically. In the next section we show that the large swings in factor exposures indeed coincide with active changes in country allocations and is not simply the result from portfolio inertia.

C. Country allocation

In order to show that the change in fixed income factor exposures around the euro crisis was an active choice, we estimate rolling betas with a vulnerable country index as well as a triple-A rated country index. We construct the vulnerable country index as the equally weighted return on 10-year zero-coupon bonds for the following five countries: Greece, Ireland, Italy, Portugal, and Spain. The distinction between vulnerable and non-vulnerable countries is based on the definition in Altavilla et al. (2016).[23] The triple-A rated country index is constructed as the equally weighted return on 10-year zero-coupon bonds for the following

[23]Cyprus is not included here as Bloomberg does not provide data for Cyprus on zero-coupon 10-year government bonds.

eight countries: Austria, Denmark, Finland, Germany, Netherlands, Norway, Sweden, and Switzerland.

Figure 4 shows the time variation in the exposures to both indices. First, we see that pension funds increased their exposure to the vulnerable index sharply in 2009 from -0.3 to 0.2, to potentially profit from carry trades. Acharya and Steffen (2015) find a similar increase in investments to vulnerable countries from March to December 2010 for eurozone banks.[24] Second, we observe that pension funds generally had non-zero exposures to the vulnerable index until the height of the euro sovereign debt crisis in 2012. The exposure moved to zero thereafter. This movement to zero shows that pension funds actively retracted their fixed income investments from the vulnerable countries following the crisis. Third, the exposure to the triple-A rated index increased significantly as of the peak of the euro sovereign debt crisis, which confirms the flight-to-quality behavior (Acharya and Steffen 2015). Fourth, the exposures to the vulnerable country index and the triple-A rated index move in opposite directions prior to the peak of the euro crisis. This movement again confirms that pension funds actively change their country allocations.

As additional evidence for active reallocation across countries we also analyze country holdings over the period from 2006Q1-2017Q4 for a sample of 42 pension funds that mandatorily report their country holdings to DNB. For fixed income, we have country allocations both in market values and in nominal values as of 2009Q1. Figure 5 summarizes the findings and shows the fraction invested in triple-A rated and vulnerable countries over time, both in market as well as in nominal values. Nominal values are useful, as these are unaffected by prices. We compare the findings to Figure 4. The country allocation also confirms that pension funds increased their allocation to vulnerable countries until 2010 and then sharply reduced their allocation, while we observe the opposite effects for the triple-A countries. Additionally, Table 16 in the Internet Appendix D shows the fraction

[24] Regulation plays a key role in the early retraction of sovereign bond investments from vulnerable countries by Dutch pension funds compared to eurozone banks. In contrast to eurozone banks, Dutch pension funds are not allowed to assign zero-risk weights to non investment grade sovereign bonds. Government bonds from countries with lower ratings get higher risk weights (www.toezicht.dnb.nl/2/50-202270.jsp).

of fixed income invested in the 13 countries that we analyze using market values, while Table 17 shows the total amount invested in each of the countries in nominal values. A few striking patterns emerge from the tables. For instance, the average holdings for Greece went down from approximately 250 million in mid 2011 to only 2 million by the second half of 2012, and for Spain the average allocation of 1,000 million went down to approximately 500 million over the same period (nominal values). In sum, these findings show that pension funds adjust their investment strategies following innovations in the news about assets with similar characteristics as their liabilities.

Table 15 in Internet Appendix D shows the results for equities. For equities we analyze the country allocation to all countries used to construct the carry factor in Koijen et al. (2018) (Australia, Canada, France, Germany, Hong Kong, Italy, Japan, Netherlands, Spain, Sweden, Switzerland, the UK, and the US). With the exceptions of a sharp increase in the allocation to Japan in 2012, a sharp drop in the allocation to the US in April 2008, and a sharp increase in the allocation to the UK from 2008 to 2009, we observe that the country allocation is fairly constant over time, which is consistent with the stable factor exposures over time. However, the changes in allocations to the UK and the US do coincide with changes in exposures to value, carry, and low beta in 2008. The increase in the allocation to Japan coincides with a drop in the exposure to low beta. Moreover, consistent with the increase in the exposure to the global market factor over time, we also observe a relative increase in US equity holdings over time. Although to a smaller extent, the effects of active reallocation across countries are therefore also visible here.

[Place Figure 5 about here]

VII. Conclusion

In this paper, we provide insight into the investment strategies of liability-driven investors that represent a large fraction of the European market for pension funds' assets. Studying factor exposures is key to understanding the heterogeneity in the performance and investment strategies of liability-driven investors.

We report the following key results. First, we find substantial heterogeneity in both equity and fixed income factor exposures across pension funds that results in economically important differences in the expected returns and thus in the beneficiaries' expected purchasing power: the heterogeneity in factor exposures that is not explained by differences in the funding ratio, risk-aversion, and liability structure reflects an annual expected return difference of 1.04 percentage points between the pension funds with the highest and those with the lowest factor exposures. This is equivalent to a difference in expected retirement income of 24 percent over a 40-year accrual phase. Second, we find a large time variation in the fixed income factor exposures due to active changes in country allocations. This variation shows that liability-driven investors adjust their investment strategies following innovations in the news about assets with similar characteristics as their liabilities.

Our results have important policy implications. Based on our findings, we argue that institutional investors in a regulated environment should actively consider the role of liability-driven investment strategies. Consequently, we suggest implementing liability-driven investment strategies as an integral part of top-down strategic investment decision-making. Further, institutional investors should explain this strategy in a clear and transparent way to their stakeholders.

VIII. Appendix

A Model derivation

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

$$\max_{w_t} = \max_{w_t} \mathbb{E}_t\left[\frac{A_{t+1}-L_{t+1}}{A_t}\right] - \frac{\gamma}{2}\mathrm{Var}_t\left[\frac{A_{t+1}-L_{t+1}}{A_t}\right], \tag{31}$$

subject to

$$w_t'\iota_N \leq c, \tag{32}$$

$$w_{i,t} \geq 0 \ \ \forall i, \tag{33}$$

where the assets equal $A_{t+1} = \Big(1 + w_t' r_{t+1}\Big)A_t$, the liabilities equal $L_{t+1} = \Big(1 + \psi r^b_{t+1}\Big)L_t$, and the funding ratio equals $F_t = A_t/L_t$.

The Lagrange of this optimization problem equals:

$$\begin{aligned}\mathcal{L}(w_t,\lambda_t) &= 1 + w_t'\mathbb{E}_t[r_{t+1}] - \Big(1+\psi\mathbb{E}_t[r^b_{t+1}]\Big)F_t^{-1} \\ &- \frac{\gamma}{2}\Big(w_t'\mathrm{Var}_t[r_{t+1}]w_t + \psi^2\mathrm{Var}_t[r^b_{t+1}]F_t^{-2} - 2w_t'\mathrm{Cov}_t(r^b_{t+1}\iota_N, r_{t+1})\psi\iota_N F_t^{-1}\Big) \\ &+ \lambda_t(w_t'\iota_N - c) + \delta_t' w_t. \end{aligned} \tag{34}$$

Taking the derivative with respect to w_t and λ_t gives:

$$\begin{aligned}\frac{\partial\mathcal{L}(w_t,\lambda_t)}{\partial w_t} &= \mathbb{E}_t[r_{t+1}] - \gamma\mathrm{Var}_t[r_{t+1}]w_t + \gamma\mathrm{Cov}_t(r^b_{t+1}\iota_N, r_{t+1})\psi\iota_N F_t^{-1} \\ &+ \lambda_t\iota_N + \delta_t = 0, \end{aligned} \tag{35}$$

$$\frac{\partial\mathcal{L}(w_t,\lambda_t)}{\partial\lambda_t} = w_t'\iota_N - c = 0. \tag{36}$$

This results in the optimal weights (7):

$$w_t^* = \underbrace{\frac{\mathbb{E}_t[r_{t+1}] + \lambda_t \iota_N + \delta_t}{\gamma \mathrm{Var}_t[r_{t+1}]}}_{\text{speculative portfolio}} + \underbrace{\frac{\mathrm{Cov}_t(r^b_{t+1}\iota_N, r_{t+1})\psi\iota_N}{\mathrm{Var}_t[r_{t+1}]} F_t^{-1}}_{\text{hedging portfolio}}$$

with λ_t:

$$\lambda_t = \frac{c - \left(\frac{\mathbb{E}_t[r_{t+1}]+\delta_t}{\gamma \mathrm{Var}_t[r_{t+1}]}\right)' \iota_N - \left(\frac{\mathrm{Cov}_t(r^b_{t+1}\iota_N, r_{t+1})\psi\iota_N}{\mathrm{Var}_t[r_{t+1}]} F_t^{-1}\right)' \iota_N}{\left(\frac{\iota_N}{\gamma \mathrm{Var}_t[r_{t+1}]}\right)' \iota_N}. \tag{36}$$

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 14 in the Internet Appendix A. 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:

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

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

$$P_{i,t+1}^{\tau-1,syn} = \frac{1}{(1+y_{i,t+\tau})^{T-\tau}}, \tag{38}$$

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

$$r_{i,t}^{syn} = \Big(\frac{(1+r_{i,t}^{f})(1+y_{i,t})^{T}}{(1+y_{i,t+\tau})^{T-\tau}} - 1\Big) \times \Big(1 + \frac{e_{i,t+1} - e_{i,t}}{e_{i,t}}\Big) \tag{39}$$

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 $i = 1, ..., J$ at time t with signal S_{it} (value, momentum, carry, or low beta), we weight securities in proportion to their cross-sectional rank based on the signal minus the cross-sectional average rank of that signal:

$$w_{it}^{S} = c_t(\text{rank}(S_{it}) - \sum_{i=1}^{J}\text{rank}(S_{it})/J), \quad \text{where } S \in (\text{value, momentum, carry, low beta}). \tag{40}$$

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):

$$C_{it} = \frac{(1 + y^{T}_{i,t})^{T}}{(1 + r^{f}_{i,t})(1 + y^{T-\tau}_{i,t})^{T-\tau}}. \tag{41}$$

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

$$\hat{\beta}_i = \hat{\rho}\frac{\hat{\sigma}_i}{\hat{\sigma}_m}, \tag{42}$$

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:

$$r^{S}_t = \sum_{i=1}^{J} w^{S}_{it-1} r^{syn}_{it}, \quad \text{where } S \in (\text{value, momentum, carry}). \tag{43}$$

The factor return for low beta is constructed as:

$$r^{\mathrm{S}}_t = \frac{1}{\beta^{L}_{t-1}}(r^{L}_t - r^{f}_t) - \frac{1}{\beta^{H}_{t-1}}(r^{H}_t - r^{f}_t), \quad \text{where } S \in (\text{low beta}), \tag{44}$$

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

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Table 1. **Total assets under management and number of pension funds**: This table shows the total AUM in billion euros of all pension funds that report (left column) and the pension funds that report at least 24 quarters (right column). The total AUM and numbers of pension funds are calculated at the end of each year.

year	**AUM all**	**number**	**AUM included**	**number**
1999	463.70	663	408.48	257
2000	480.78	676	442.98	335
2001	471.00	656	436.77	352
2002	429.51	658	399.27	374
2003	489.60	642	458.86	376
2004	529.93	605	507.73	389
2005	610.52	575	574.91	334
2006	657.57	524	591.27	346
2007	683.53	442	663.60	364
2008	576.32	413	555.10	349
2009	663.59	376	630.34	322
2010	746.28	350	727.40	318
2011	802.33	329	782.50	290
2012	897.09	260	737.55	282
2013	937.12	258	835.65	241
2014	1,131.74	247	1,083.63	228
2015	1,146.66	227	1,086.12	195
2016	1,262.54	216	1,205.90	190
2017	1,224.07	200	1,163.47	175

Table 2. **Summary statistics**: Panel A reports the summary statistics for pension fund returns, both equally and value weighted. The mean returns and standard deviations of returns are measured across time and pension funds for 1999Q1-2017Q4. We also report the means and standard deviations for equity and fixed income allocations (percent), duration (years), funding ratio (percent, as of 2007), required funding ratio (percent, 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	19.30	−0.62	3.88
Excess return fixed income	3.87	7.98	0.52	6.39
Value weighted				
Excess return equity	4.79	18.18	−0.51	4.27
Excess return fixed income	3.71	6.84	0.61	6.59
Characteristics				
Equity allocation	31.00	9.14		
Fixed income allocation	58.76	11.78		
Duration fixed income portfolio	8.20	8.71		
Funding ratio	115.77	15.99		
Required funding ratio	115.35	12.61		
Ratio to actives	64.25	24.89		

Panel B: Factor returns

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

Table 3. **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 4. **Unconditional - OLS factor exposures**: This table displays the cross-sectional mean and standard deviation of the estimated betas from the time-series regression presented in Equation (14). The cross-sectional mean and standard deviation of the R-squared from the time-series regressions are also provided. 10%-level and 5%-level sign. indicate the number of pension funds for which the corresponding factor is statistically different from zero at the 10% and 5% significance level, respectively, by using the Newey-West adjusted standard errors. M,W indicates the MSCI World Total Return Index, M,EU indicates the excess Euro Stoxx 50 Total Return Index for equities and the excess Bloomberg Barclays Euro Aggregate Total Return Bond Index for fixed income, HY-EU indicates the excess Bloomberg Barclays Euro High Yield Index, VAL indicates the value factor for the corresponding asset class, MOM indicates the momentum factor for the corresponding asset class, CARRY indicates the carry factor for the corresponding asset class, and BAB indicates the low beta factor for the corresponding asset class.

Equity returns				
	mean	std.dev.	10%-level sign.	5%-level sign.
$\hat{\beta}_i^{M,W}$	0.6607	0.2178	416	413
$\hat{\beta}_i^{M,EU}$	0.2811	0.1872	370	350
$\hat{\beta}_i^{VAL}$	−0.0458	0.1352	129	89
$\hat{\beta}_i^{MOM}$	−0.0453	0.1059	126	93
$\hat{\beta}_i^{CARRY}$	−0.0597	0.2402	131	82
$\hat{\beta}_i^{BAB}$	0.0939	0.1476	219	183
R^2	0.9198	0.0940		
Fixed income returns				
	mean	std.dev.	10%-level sign.	5%-level sign.
$\hat{\beta}_i^{M,EU}$	1.2144	0.4604	426	423
$\hat{\beta}_i^{HY,EU}$	0.0170	0.1042	175	148
$\hat{\beta}_i^{VAL}$	−0.1979	0.2425	188	146
$\hat{\beta}_i^{MOM}$	0.0640	0.2232	70	46
$\hat{\beta}_i^{CARRY}$	−0.0404	0.3915	79	53
$\hat{\beta}_i^{BAB}$	0.2555	0.3750	214	173
R^2	0.7135	0.1750		

Table 5. **Unconditional - prior factor exposures**: This table shows the coefficient estimates and corresponding standard errors for the random-coefficients model in Equation (15) that is used as a prior to compute the posterior betas. The estimates $\hat{\alpha}$ and $\hat{\beta}^k$ indicate the fixed effects, and $\hat{\sigma}^2_{\alpha}$, and $\hat{\sigma}^2_k$ indicate the random effects of the random-coefficients model. M,W indicates the MSCI World Total Return Index, M,EU indicates the excess Euro Stoxx 50 Total Return Index for equities and the excess Bloomberg Barclays Euro Aggregate Total Return Bond Index for fixed income, HY-EU indicates the excess Bloomberg Barclays Euro High Yield Index, VAL indicates the value factor for the corresponding asset class, MOM indicates the momentum factor for the corresponding asset class, CARRY indicates the carry factor for the corresponding asset class, and BAB indicates the 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
$\hat{\alpha}$	-0.0012^{***}	0.0003	$\hat{\alpha}$	0.0013^{***}	0.0002
$\hat{\beta}^{M,W}$	0.6553^{***}	0.0095	$\hat{\beta}^{M,EU}$	1.2065^{***}	0.0206
$\hat{\beta}^{M,EU}$	0.2964^{***}	0.0082	$\hat{\beta}^{HY,EU}$	0.0201^{***}	0.0052
$\hat{\beta}^{VAL}$	-0.0405^{***}	0.0059	$\hat{\beta}^{VAL}$	-0.2107^{***}	0.0095
$\hat{\beta}^{MOM}$	-0.0404^{***}	0.0044	$\hat{\beta}^{MOM}$	0.0704^{***}	0.0081
$\hat{\beta}^{CARRY}$	-0.0371^{***}	0.0101	$\hat{\beta}^{CARRY}$	-0.0801^{***}	0.0126
$\hat{\beta}^{BAB}$	0.0986^{***}	0.0066	$\hat{\beta}^{BAB}$	0.2836^{***}	0.0130
$\hat{\sigma}^2_{\alpha}$	0.00001^{**}	0.0000001	$\hat{\sigma}^2_{\alpha}$	0.0000004	0.000002
$\hat{\sigma}^2_{M,W}$	0.0269^{***}	0.0038	$\hat{\sigma}^2_{M,EU}$	0.1483^{***}	0.0278
$\hat{\sigma}^2_{M,EU}$	0.0196^{***}	0.0024	$\hat{\sigma}^2_{HY,EU}$	0.0075^{***}	0.0012
$\hat{\sigma}^2_{VAL}$	0.0078^{***}	0.0028	$\hat{\sigma}^2_{VAL}$	0.0226^{***}	0.0043
$\hat{\sigma}^2_{MOM}$	0.0021^{**}	0.0011	$\hat{\sigma}^2_{MOM}$	0.0013	0.0028
$\hat{\sigma}^2_{CARRY}$	0.0191^{***}	0.0054	$\hat{\sigma}^2_{CARRY}$	0.0063^{*}	0.0057
$\hat{\sigma}^2_{BAB}$	0.0097^{***}	0.0021	$\hat{\sigma}^2_{BAB}$	0.0475^{***}	0.0231
$\hat{\sigma}_{M,WM,EU}$	-0.0203^{***}	0.0027			
Wald chi2(6)	49,513.40		Wald chi2(6)	6,750.38	

Table 6. **Unconditional - posterior factor exposures**: This table displays the cross-sectional means and standard deviations of the posterior betas from Equation (17), which are approximately normally distributed. M,W indicates the MSCI World Total Return Index, M,EU indicates the excess Euro Stoxx 50 Total Return Index for equities and the excess Bloomberg Barclays Euro Aggregate Total Return Bond Index for fixed income, HY-EU indicates the excess Bloomberg Barclays Euro High Yield Index, VAL indicates the value factor for the corresponding asset class, MOM indicates the momentum factor for the corresponding asset class, CARRY indicates the carry factor for the corresponding asset class, and BAB indicates the low beta factor for the corresponding asset class.

Equity returns			Fixed income returns		
	mean	std.dev.		mean	std.dev.
$\tilde{\beta}_i^{M,W}$	0.6674	0.1501	$\tilde{\beta}_i^{M,EU}$	1.1627	0.2658
$\tilde{\beta}_i^{M,EU}$	0.2821	0.1292	$\tilde{\beta}_i^{HY,EU}$	0.0238	0.0592
$\tilde{\beta}_i^{VAL}$	−0.0464	0.0506	$\tilde{\beta}_i^{VAL}$	−0.1692	0.1037
$\tilde{\beta}_i^{MOM}$	−0.0430	0.0251	$\tilde{\beta}_i^{MOM}$	0.0639	0.0167
$\tilde{\beta}_i^{CARRY}$	−0.0412	0.0950	$\tilde{\beta}_i^{CARRY}$	−0.0723	0.0358
$\tilde{\beta}_i^{BAB}$	0.0840	0.0675	$\tilde{\beta}_i^{BAB}$	0.2236	0.1487

Table 7. **Unconditional - heterogeneity of expected returns**: This table shows the distribution of the expected return contributions of 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 contribution of all factors equals $\sum_{k=1}^{K} \tilde{\beta}_i^k \lambda^k$. The contribution of the market exposure to the total expected return is computed as $\tilde{\beta}_i^{M\prime} \lambda^M = \tilde{\beta}_i^{M,W} \lambda^{M,W} + \tilde{\beta}_i^{M,EU} \lambda^{M,EU}$ for equities and $\tilde{\beta}_i^{M\prime} \lambda^M = \tilde{\beta}_i^{M,EU} \lambda^{M,EU} + \tilde{\beta}_i^{HY,EU} \lambda^{HY,EU}$ for fixed income. The contribution of the long-short factors to total expected returns is computed as $\tilde{\beta}_i^k \lambda^k$ for each long-short factor k. 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 10th, 10th-40th, 40th-60th, 60th-90th, and 90th-100th percentiles. All values are percentage points and annualized.

Panel A: Equity

	10th	10th-40th	40th-60th	60th-90th	90th-100th
Contribution of all factors	2.27	4.05	4.85	5.46	6.53
Contribution of market factors	4.05	4.44	4.52	4.53	4.70
Contribution of value	−0.32	−0.22	−0.13	−0.17	−0.10
Contribution of momentum	−0.28	−0.24	−0.22	−0.21	−0.18
Contribution of carry	−1.11	−0.58	−0.22	0.05	0.36
Contribution of low beta	−0.08	0.63	0.89	1.26	1.76

Panel B: Fixed income

	10th	10th-40th	40th-60th	60th-90th	90th-100th
Contribution of all factors	1.92	2.62	2.99	3.38	3.89
Contribution of market factors	2.07	2.73	3.08	3.52	4.04
Contribution of value	−0.15	−0.13	−0.18	−0.25	−0.29
Contribution of momentum	0.08	0.07	0.08	0.09	0.09
Contribution of carry	−0.14	−0.12	−0.12	−0.14	−0.14
Contribution of low beta	0.07	0.08	0.12	0.17	0.19

Panel C: Overall portfolio

	10th	10th-40th	40th-60th	60th-90th	90th-100th
Contribution of all factors	2.43	3.12	3.64	4.09	4.69
Contribution of market factors	2.84	3.31	3.64	3.88	4.05
Contribution of long-short factors	−0.41	−0.19	0.01	0.21	0.65

Table 8. **Unconditional - variance decomposition**: This table shows how much of the variance in estimated average returns $\tilde{\mu}$ is explained by the alpha and the factor exposures for equities and fixed income presented in Equation (22). We calculate the average return per asset class of each pension fund using $\tilde{\mu}_i = \tilde{\alpha}_i + \tilde{\beta}_i' \lambda_i$ in which λ_i is the average factor return over the period in which pension fund i is in the sample.

Variance contribution			
Equity returns		Fixed income returns	
α	−0.04	α	3.67
Market World	68.87	Market EU	91.77
Market EU	15.13	High yield EU	5.43
Value	5.46	Value	−10.07
Momentum	0.69	Momentum	2.54
Carry	5.74	Carry	−4.54
Low beta	8.14	Low beta	11.20

Table 9. **Factor exposures of liability returns**: This table shows the cross-sectional average factor exposures and the corresponding t statistics for the liability returns. M,W indicates the MSCI World Total Return Index, M,EU indicates the excess Euro Stoxx 50 Total Return Index for equities, and the excess Bloomberg Barclays Euro Aggregate Total Return Bond Index for fixed income, HY-EU indicates the excess Bloomberg Barclays Euro High Yield Index, VAL indicates the value factor for the corresponding asset class, MOM indicates the momentum factor for the corresponding asset class, CARRY indicates the carry factor for the corresponding asset class, and BAB indicates the low beta factor for the corresponding asset class. Estimates are over the period 2007Q1-2017Q4 and for pension funds that appear over the full sample period (76 pension funds).

Equity factors			Fixed income factors		
	mean	t stat		mean	t stat
$\tilde{\beta}_i^{M,W}$	−0.1419	−0.0414	$\tilde{\beta}_i^{M,EU}$	2.2885	4.8675
$\tilde{\beta}_i^{M,EU}$	−0.0008	−0.3799	$\tilde{\beta}_i^{HY,EU}$	0.0316	0.2274
$\tilde{\beta}_i^{VAL}$	−0.2158	−0.8482	$\tilde{\beta}_i^{VAL}$	−0.0870	−0.1776
$\tilde{\beta}_i^{MOM}$	−0.0157	−0.4513	$\tilde{\beta}_i^{MOM}$	0.0505	0.3301
$\tilde{\beta}_i^{CARRY}$	−0.0530	−0.4686	$\tilde{\beta}_i^{CARRY}$	−0.8294	−1.7547
$\tilde{\beta}_i^{BAB}$	−0.1407	−0.8304	$\tilde{\beta}_i^{BAB}$	−0.1924	−0.3276
R^2	0.76				

Table 10. **Impact of pension fund characteristics on factor exposures for equities**: This table shows the coefficient estimates of Equation (25): We regress the pension funds' equity returns on the factor returns and the factor returns interacted with the funding ratio (FR), the risk-aversion coefficient that we represent with the inverse of the required funding ratio (risk-aversion), the liability duration that we represent with the ratio of actives relative to total participants (duration), size, and asset managers (AM1-AM5) during the period from 2009-2016. Standard errors are in parentheses and clustered at the pension fund level; $^{*}p < 0.10$, $^{**}p < 0.05$, and $^{***}p < 0.01$.

	Equity returns				
	BM	FR	risk-aversion	duration	size
$\beta^{M,W}$	0.6891***	0.0018	−0.4657*	0.0448	0.0371***
	(0.0137)	(0.0733)	(0.2597)	(0.0449)	(0.0139)
$\beta^{M,E}$	0.2685***	0.0615	0.1857	−0.0137	−0.0392***
	(0.0137)	(0.0984)	(0.2628)	(0.0471)	(0.0128)
β^{VAL}	0.0430***	−0.0734	0.2390	−0.0593	−0.0160
	(0.0136)	(0.086)	(0.2986)	(0.0383)	(0.0128)
β^{MOM}	−0.0433***	−0.0344	0.2071	−0.0141	−0.0116
	(0.0102)	(0.0491)	(0.2179)	(0.0303)	(0.0089)
β^{CARRY}	0.0285***	0.0781*	−0.2585	0.0135	−0.0011
	(0.0095)	(0.045)	(0.1862)	(0.0271)	(0.0083)
β^{BAB}	0.0618***	0.0464	−0.1190	−0.0371	0.0128*
	(0.0134)	(0.046)	(0.1853)	(0.0291)	(0.0086)
	AM1	AM2	AM3	AM4	AM5
$\beta^{M,W}$	0.0292	0.1248***	−0.0055	0.0801***	0.0896*
	(0.0241)	(0.0312)	(0.0374)	(0.0281)	(0.0517)
$\beta^{M,E}$	0.0008	−0.0750***	−0.0466	−0.0376	−0.0770
	(0.0251)	(0.0279)	(0.0391)	(0.032)	(0.052)
β^{VAL}	−0.0472*	−0.0527**	0.1999***	−0.0356*	−0.0955*
	(0.0271)	(0.0245)	(0.0311)	(0.02)	(0.051)
β^{MOM}	−0.0110	−0.0009	0.0824***	−0.0044	−0.0665**
	(0.0212)	(0.0202)	(0.0232)	(0.0283)	(0.0304)
β^{CARRY}	−0.0013	−0.0201	0.0841***	−0.0147	0.0591**
	(0.02)	(0.0184)	(0.024)	(0.0234)	(0.0261)
β^{BAB}	−0.0304	−0.0331**	0.0149	0.0001	−0.0106
	(0.0162)	(0.015)	(0.0292)	(0.0237)	(0.0245)
within R^2	88.28%		obs.	8,167	
between R^2	79.42%		N	344	
overall R^2	87.80%				

Table 11. **Impact of pension fund characteristics on factor exposures for fixed income**: This table shows the coefficient estimates of Equation (25): We regress the pension funds' fixed income returns on the factor returns and the factor returns interacted with the funding ratio (FR), the risk-aversion coefficient that we represent with the inverse of the required funding ratio (risk-aversion), the liability duration that we represent with the ratio of actives relative to total participants (duration), size, and asset managers (AM1-AM5) during the period from 2009-2016. Standard errors are in parentheses and clustered at the pension fund level; $^{*}p < 0.10$, $^{**}p < 0.05$, and $^{***}p < 0.01$.

	Fixed income returns				
	BM	FR	risk-aversion	duration	size
$\beta^{M,EU}$	2.0480***	−1.0172***	9.9402***	1.4987***	0.0809
	(0.074)	(0.3046)	(1.6009)	(0.2594)	(0.0844)
$\beta^{HY,EU}$	−0.0301***	0.1075***	−0.8043***	−0.1056***	0.0207**
	(0.0078)	(0.0343)	(0.1677)	(0.0236)	(0.0091)
β^{VAL}	−0.2330***	0.0130	−0.8843*	−0.0641	−0.0115
	(0.021)	(0.0837)	(0.4944)	(0.0618)	(0.0219)
β^{MOM}	−0.0252***	−0.0452	0.8945***	0.0522	0.0023
	(0.0115)	(0.0622)	(0.2796)	(0.0451)	(0.0146)
β^{CARRY}	−0.4163***	0.3250	−3.9867***	−0.7126***	−0.0893
	(0.0458)	(0.2158)	(1.0486)	(0.1545)	(0.0598)
β^{BAB}	−0.0101	0.0941	−1.9396**	−0.3935***	−0.0159
	(0.0329)	(0.1509)	(0.7467)	(0.1093)	(0.0349)
	AM1	AM2	AM3	AM4	AM5
$\beta^{M,EU}$	0.4282	−0.0514	0.4447**	0.3701**	0.5430*
	(0.2663)	(0.1363)	(0.1931)	(0.1839)	(0.2982)
$\beta^{HY,EU}$	0.0265*	0.0040	0.0226	−0.0829***	−0.0824***
	(0.0139)	(0.0136)	(0.0223)	(0.0164)	(0.029)
β^{VAL}	0.0774	0.1442***	0.1377**	0.1060**	−0.0326
	(0.0901)	(0.0344)	(0.0631)	(0.0441)	(0.0795)
β^{MOM}	0.0897	0.0385	0.0482	0.0620*	0.0013
	(0.0573)	(0.0243)	(0.0444)	(0.037)	(0.0442)
β^{CARRY}	−0.3482*	−0.0992	−0.4456***	−0.3034**	−0.0276
	(0.2007)	(0.08)	(0.1332)	(0.1341)	(0.1721)
β^{BAB}	−0.1368	−0.1101*	−0.2468**	−0.1404	0.0393
	(0.1005)	(0.0586)	(0.0999)	(0.0953)	(0.1343)
within R^2	56.46%		obs.	8,229	
between R^2	33.01 %		N	344	
overall R^2	55.89%				

Table 12. **Unconditional - heterogeneity of expected returns adjusted for liability hedge demand**: This table shows the distribution of the expected return contributions of market factors, long-short factors, and all factors to the overall portfolio returns. 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 10th, 10th-40th, 40th-60th, 60th-90th, and 90th-100th percentiles. All values are percentage points and annualized.

Overall portfolio					
	10th	10th-40th	40th-60th	60th-90th	90th-100th
Contribution of all factors	3.07	3.45	3.75	3.95	4.11
Contribution of market factors	3.11	3.46	3.54	3.77	3.75
Contribution of long-short factors	−0.04	0.01	0.21	0.18	0.36

Table 13. **Unconditional - 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 (30). We report the 10th, 25th, 50th, 75th, and 90th percentiles. All values are in percentages and annualized.

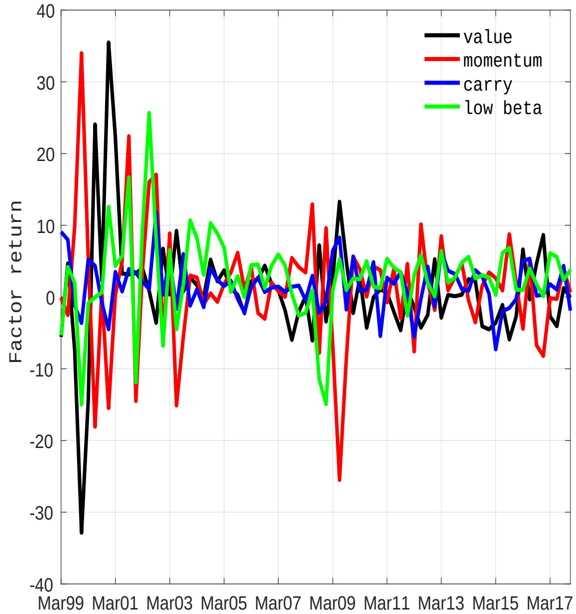
Panel A: Equity returns

	mean	**10th**	**25th**	**50th**	**75th**	**90th**
benchmark return	4.99					
implied beliefs world market index	4.99	−1.60	−0.95	−0.29	0.23	0.74
implied beliefs European market index	4.07	−0.24	0.61	1.37	1.95	2.69
Implied beliefs value	4.00	−0.44	0.12	0.52	0.91	1.39
Implied beliefs momentum	5.20	−1.08	−0.76	−0.49	−0.22	0.11
Implied beliefs carry	6.49	−0.53	−0.40	−0.25	−0.12	0.01
Implied beliefs low beta	11.03	−0.15	0.18	0.53	0.83	1.13

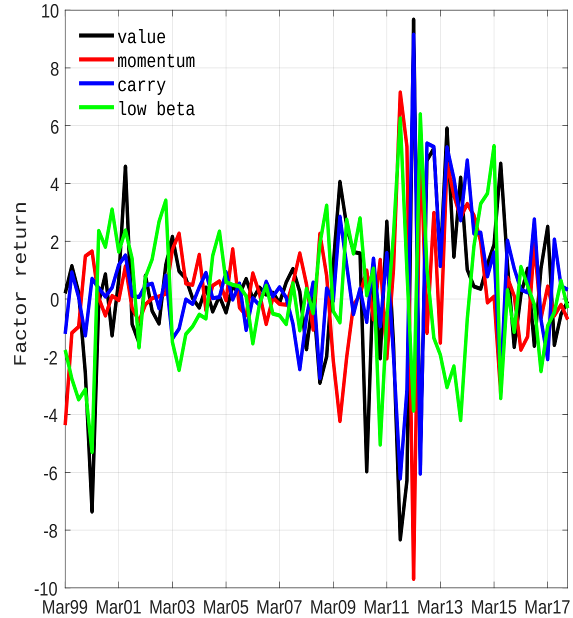
Panel B: Fixed income returns

	mean	**10th**	**25th**	**50th**	**75th**	**90th**
benchmark return	2.55					
implied beliefs market index	2.55	−0.33	−0.19	−0.07	0.06	0.19
implied beliefs high yield	6.38	−1.19	−0.83	−0.33	0.14	0.56
Implied beliefs value	1.17	−0.70	−0.59	−0.48	−0.33	−0.12
Implied beliefs momentum	1.24	0.08	0.18	0.29	0.38	0.43
Implied beliefs carry	1.84	−0.39	−0.33	−0.28	−0.21	−0.12
Implied beliefs low beta	0.86	0.09	0.29	0.49	0.65	0.81

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.

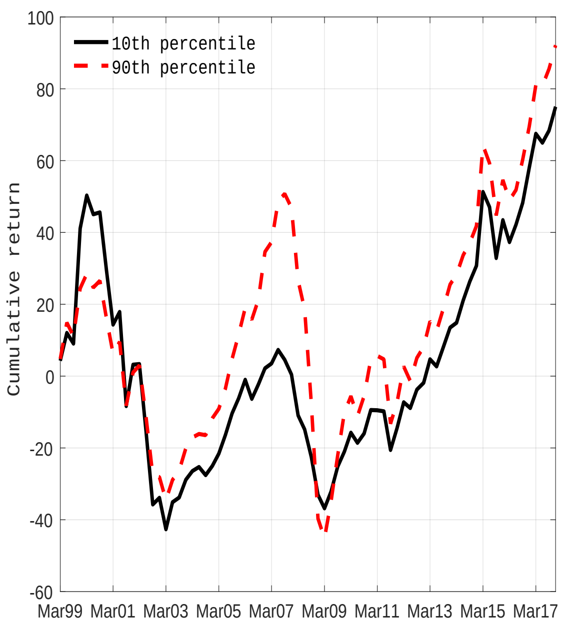


Equities factors

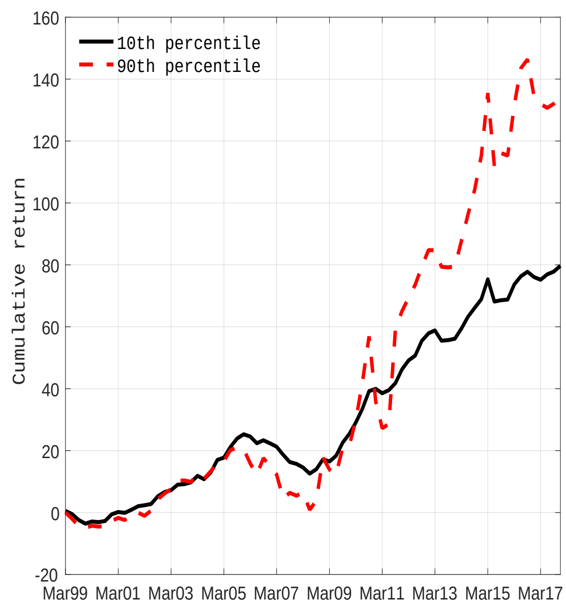


Fixed income factors

Figure 2. **Cumulative pension fund returns**: This figure shows the realized cumulative returns of pension funds with the highest aggregate factor exposures (90th percentile) compared to those with the lowest (10th percentile) over our sample period, 1999Q1-2017Q4. We only include pension funds that are in the sample over the entire period.

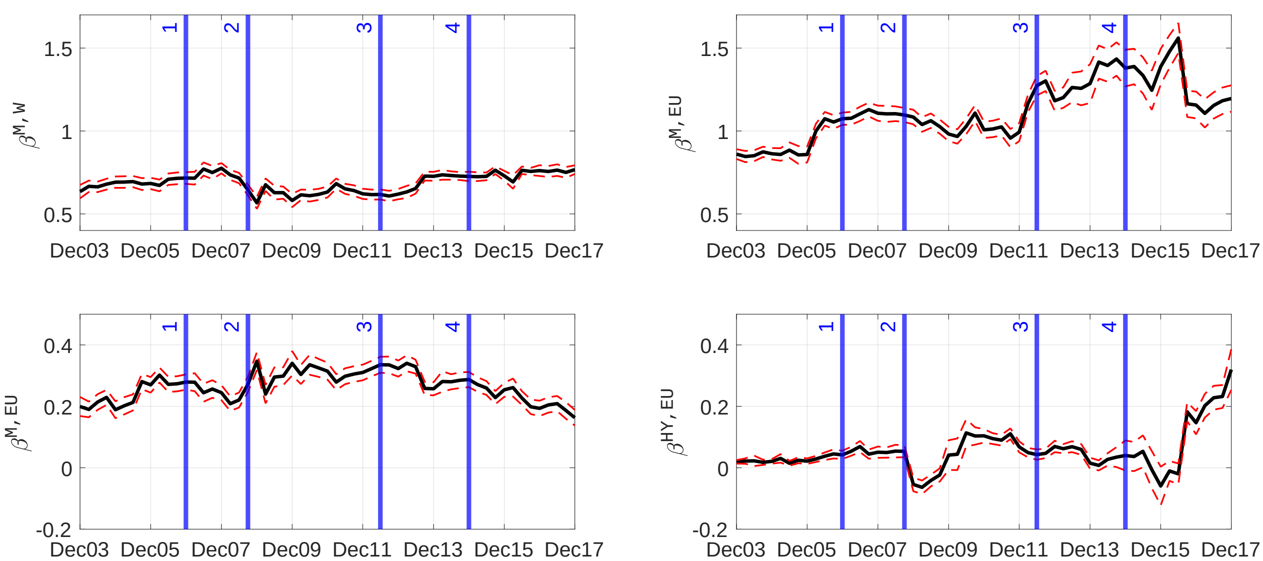


Equities factors



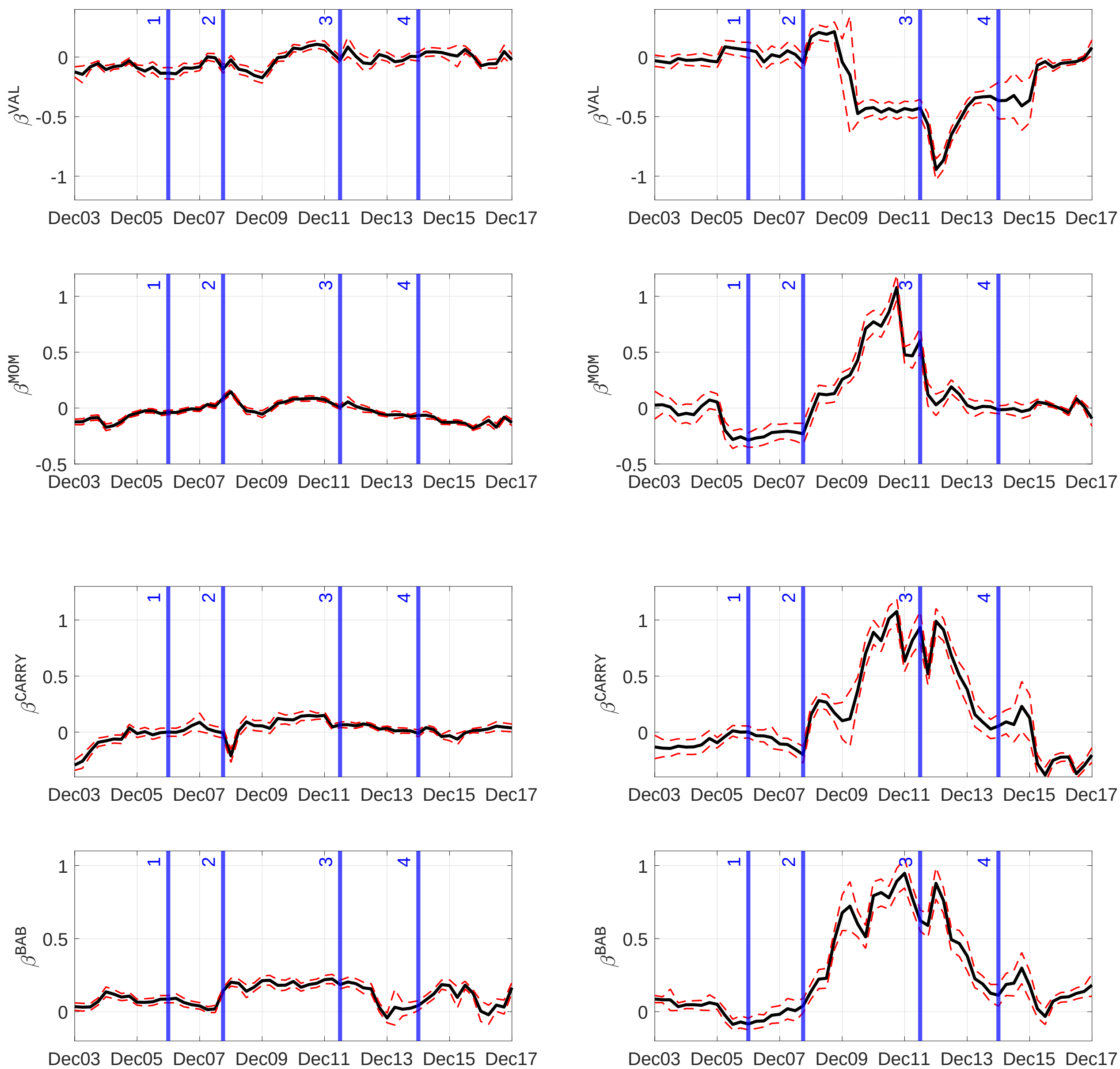
Fixed income factors

Figure 3. **Conditional - rolling betas**: This figure shows the cross-sectional average rolling window factor exposures for equities (left columns) and fixed income (right columns) over the period 2005Q1-2017Q4. The estimates are based on a 20-quarter rolling window. The graphs show the cross-sectional average factor exposures (black solid line) and the corresponding 95 percent confidence interval (dashed lines). Panel A shows the results for the market factors and the credit factor for fixed income. Panel B shows the results for the long-short factors. The blue vertical lines represent four key events during our sample: (1) the introduction of risk-based pension fund regulation on January 1, 2007, (2) the start of the Great Financial Crisis with the collapse of the investment bank Lehman Brothers on September 15, 2008, (3) the announcement of the government of Cyprus that it would seek a bailout from the European Union (EU) and the International Monetary Fund (IMF) on June 25, 2012, (4) and a change in pension fund regulation on January 1, 2015. M,W indicates the MSCI World Total Return Index, M,EU indicates the excess Euro Stoxx 50 Total Return Index for equities, and the excess Bloomberg Barclays Euro Aggregate Total Return Bond Index for fixed income, HY-EU indicates the excess Bloomberg Barclays Euro High Yield Index, VAL indicates the value factor for the corresponding asset class, MOM indicates the momentum factor for the corresponding asset class, CARRY indicates the carry factor for the corresponding asset class, and BAB indicates the low beta factor for the corresponding asset class.



Equities factors **Fixed income factors**

Panel A: Market factors and fixed income credit factor



Equities factors | **Fixed income factors**

Panel B: Long-short factors

Figure 4. **Conditional - exposures to a vulnerable and a triple-A country index**: This figure shows the cross-sectional average rolling window exposures of the *vulnerable country index* ($\beta^{\text{vulnerable}}$) and the *triple-A country index* ($\beta^{\text{triple-A}}$) for fixed income over the period from 2002Q4-2017Q4. The estimates are based on a 20-quarter rolling window. The graphs show the cross-sectional average factor exposures (black solid line) and the corresponding 95 percent confidence interval (dashed lines). The blue vertical lines represent four key events during our sample: (1) the introduction of risk-based pension fund regulation on January 1, 2007, (2) the start of the Great Financial Crisis with the collapse of the investment bank Lehman Brothers on September 15, 2008, (3) the announcement of the government of Cyprus that it will seek a bailout from the European Union (EU) and the International Monetary Fund (IMF) on June 25, 2012, (4) and a change in pension fund regulation on January 1, 2015.

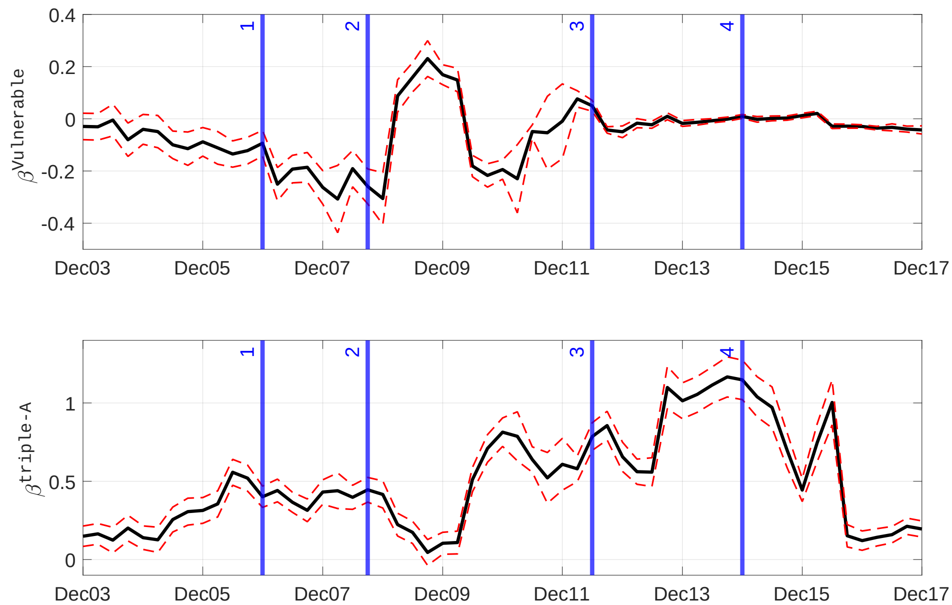
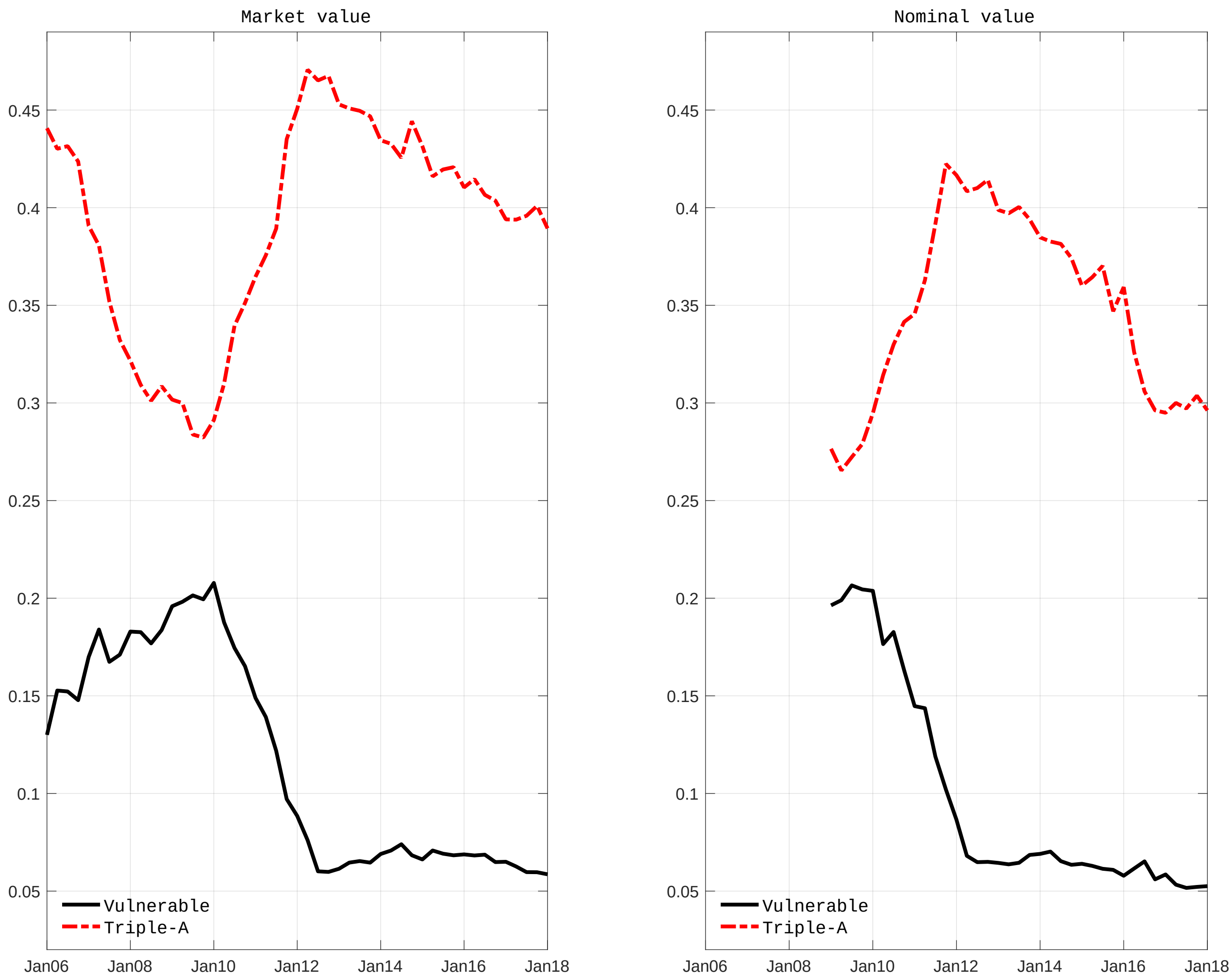


Figure 5. **Holdings in vulnerable and triple-A countries**: This figure shows the average fraction of vulnerable and triple-A countries in the fixed income portfolio based on market and nominal values over the period from 2005Q1-2017Q4.



IX. Internet Appendix

A Bloomberg ticker list

Table 14. **Bloomberg ticker list**: This table contains 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

B Random-Coefficients Model

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

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

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

$$G = \mathbb{E}(v_k v_j') = \begin{cases} \sigma^2_{\beta^k} & \text{for} \quad j = k \\ \sigma_{\beta^k \beta^j} & \text{for} \quad j \neq k \end{cases} \tag{45}$$

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.[25]

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

To derive the likelihood, we start with writing Equation (15) in vector notation:[26]

$$r_i^e = \alpha\iota_T + \beta' f + v_i' f + u_i + \epsilon_i, \tag{46}$$

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:

$$\mathrm{Var}\begin{bmatrix} \alpha_i \\ v_i^1 \\ .. \\ v_i^K \\ \epsilon_i \end{bmatrix} = \begin{bmatrix} \sigma_\alpha^2 \iota_T\ \iota_T' & 0 & 0 & 0 & 0 \\ 0 & \sigma_{\beta^1}^2 \iota_T \iota_T' & \sigma_{\beta^1\beta^2} \iota_T \iota_T' & 0 & 0 \\ 0 & \sigma_{\beta^2\beta^1} \iota_T \iota_T' & \ddots & 0 & 0 \\ 0 & 0 & 0 & \sigma_{\beta^K}^2 \iota_T \iota_T' & 0 \\ 0 & 0 & 0 & 0 & \sigma_\epsilon^2 \mathbf{I}_T \end{bmatrix}. \tag{47}$$

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

$$V = \mathrm{Var}[r_i^e | f] = \sigma_\alpha^2 \iota_T\ \iota_T' + \sigma_{\beta^1}^2 f^1 f^{1'} + 2\sigma_{\beta^1\beta^2} f^1 f^{2'} + \sigma_{\beta^2}^2 f^2 f^{2'} + ... + \sigma_{\beta^K}^2 f^K f^{K'} + \sigma_\epsilon^2 \mathbf{I}_T. \tag{48}$$

[25] 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.

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

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

$$L_i(\alpha, \beta, \sigma_\alpha^2, \sigma_{\beta^1}^2, ..., \sigma_{\beta^K}^2, \sigma_\epsilon^2 | r_i^e) = -\frac{1}{2}\{T \log(2\pi) + \log|V| + (r_i^e - \alpha\iota_T - \beta' f)' V^{-1} (r_i^e - \alpha\iota_T - \beta' f)\}. \tag{49}$$

Then, the total log-likelihood equals:

$$L(\alpha, \beta, \sigma_\alpha^2, \sigma_{\beta^1}^2, ..., \sigma_{\beta^K}^2, \sigma_\epsilon^2 | r^e) = -\frac{1}{2}\{NT \log(2\pi) + N \log|V| + \sum_{i=1}^{N} (r_i^e - \alpha\iota_T - \beta' f)' V^{-1} (r_i^e - \alpha\iota_T - \beta' f)\}. \tag{50}$$

We now turn to a detailed description of the estimation results described in Table 5. We begin by analyzing the results for equities. The exposure to the global market factor equals 0.66, 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 0.33 and 0.98, and the exposure to the European market factor varies between 0.02 and 0.57. Pension funds on average have significantly negative exposures to value (-0.04), momentum (-0.04), and carry (-0.04). Significant cross-sectional variation exists in all three factor exposures. The highest cross-sectional standard deviation equals 0.14 for the carry factor that indicates the range of factor exposures is between -0.32 and 0.25. The exposure to value varies between -0.23 and 0.14, and between -0.12 and 0.04 for momentum. Pension funds on average have a significantly positive exposure to the low beta factor that is equal to 0.10. Again, we find significant and substantial cross-sectional variation in the low beta exposure that ranges from -0.09 to 0.29.

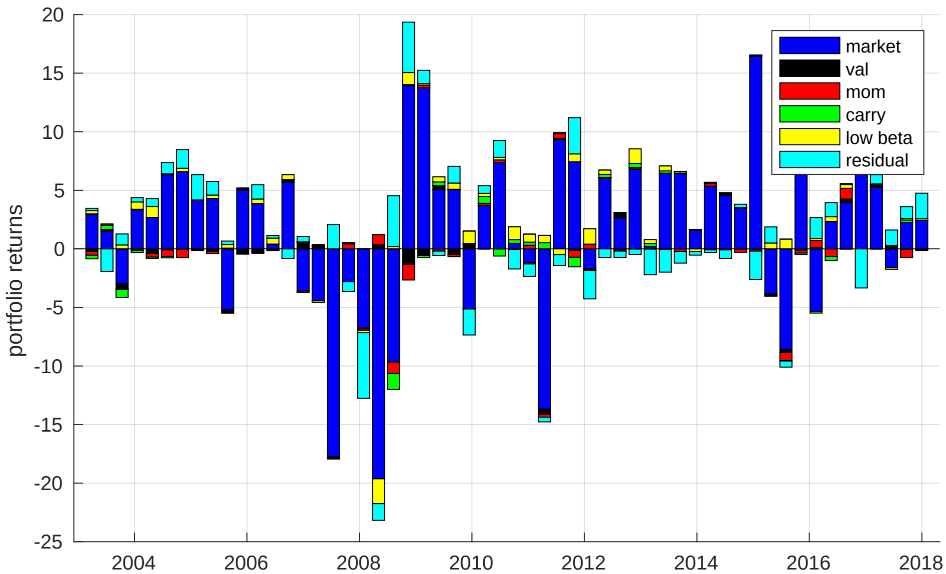
In case of fixed income, pension funds have an average (significant) exposure to the investment-grade market factor that is equal to 1.21. The cross-sectional variation ranges from 0.44 to 1.98. For the fixed income factors we find that pension funds, on average, have a negative exposure to value (-0.21) and carry (-0.08), a slightly positive exposure to momentum (0.07), and strong positive exposure to low beta (0.28). The exposure to value varies between -0.51 and 0.09, between -0.24 and 0.08 for carry, and between -0.15 and 0.72 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 10 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 0.0025, and the alphas vary between -0.0063 and -0.0037 on a quarterly basis. For fixed income we do not observe any variation in the alphas. This finding indicates that pension funds are unable to outperform each other consistently. However, even if pension funds slightly vary in their alphas, our sample might not have enough observations to say something statistically meaningful about the alphas. This finding is expected, because first moments can be estimated less accurately than second moments (Merton 1980).

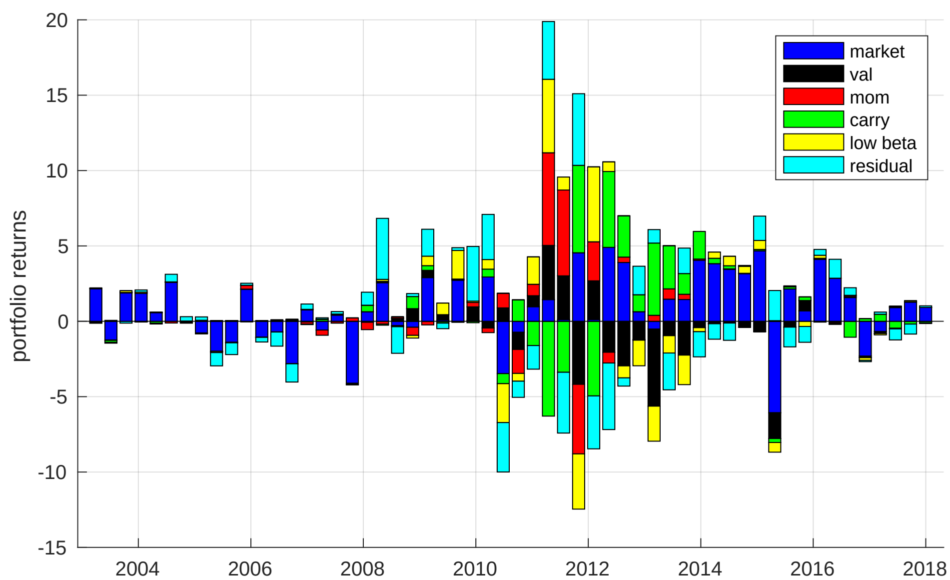
C Return decomposition

This section shows the contribution of the average factor exposures to the average realized returns. We multiply the lagged rolling beta estimates with the realized returns on the factors. The residual return in every period equals the average realized return across the pension funds in the sample minus the cross-sectional average lagged factor exposures times the realized returns on the factors.

Figure 6. **Conditional - return decomposition**: This figure shows a quarterly return decomposition for equities (Panel A) and fixed income (Panel B) based on rolling-betas estimates. The lagged rolling beta estimates at $t-1$ are multiplied by the realized returns at time t: $\bar{\beta}^k_{t-1} f^k_t$ in which $\bar{\beta}^k_{t-1}$ is the cross-sectional average exposure to factor k at time $t-1$ and f^k_t is the return on factor k at time t.



Panel A: Equities factors



Panel B: Fixed income factors

Table 15. **Country allocation equities**: This table shows the cross-sectional relative weights invested in the following countries: Australia (AU), Canada (CA), France (FR), Germany (DE), Hong Kong (HK), Italy (IT), Japan (JP), Netherlands (NL), Spain (ES), Sweden (SE), Switzerland (CH), the United Kingdom (GB), and the United States (US). The relative weights are in percent and add up to 100.

	Equity												
Date	AU	CA	FR	DE	HK	IT	JP	NL	ES	SE	CH	GB	US
Jan−06	3	2	8	6	1	3	10	17	3	2	5	12	27
Apr−06	4	2	8	7	1	3	10	18	3	2	5	12	27
Jul−06	3	1	7	5	1	3	18	16	3	2	6	11	24
Oct−06	4	1	8	6	2	3	9	18	3	2	5	14	26
Jan−07	4	1	8	7	2	3	9	17	2	2	6	14	26
Apr−07	5	2	8	8	1	2	10	15	3	2	5	14	26
Jul−07	5	2	9	6	2	3	10	14	2	2	5	13	28
Oct−07	4	2	8	8	2	3	10	13	2	2	5	12	30
Jan−08	4	2	10	8	3	3	9	11	3	2	5	13	30
Apr−08	5	3	11	6	3	3	7	11	2	2	10	14	22
Jul−08	6	3	10	4	3	3	9	9	3	2	7	12	30
Oct−08	4	2	10	9	2	2	11	10	3	1	9	10	28
Jan−09	3	2	7	6	2	2	12	8	3	1	4	16	35
Apr−09	4	2	7	6	2	2	12	7	3	1	4	18	33
Jul−09	5	2	8	6	2	3	10	7	3	2	4	15	34
Oct−09	5	3	8	6	2	2	9	7	3	1	4	16	34
Jan-10	5	3	7	5	2	2	8	7	2	2	4	15	37
Apr-10	3	3	7	6	2	2	8	7	2	2	4	16	37
Jul-10	3	3	8	6	2	2	7	7	2	2	4	16	37
Oct-10	4	3	7	6	2	2	8	8	2	2	5	15	37
Jan-11	4	3	7	6	2	2	8	8	2	2	4	15	37
Apr-11	4	3	7	6	2	2	8	7	2	2	4	14	38
Jul-11	4	3	6	5	2	2	10	8	2	2	4	14	38
Oct-11	4	3	6	5	2	2	9	7	2	2	4	14	40
Jan-12	4	3	6	6	2	2	9	6	2	2	4	14	41
Apr-12	4	3	6	5	2	1	9	7	2	2	4	14	41
Jul-12	3	3	6	5	2	1	16	6	2	2	4	12	37

Date	AU	CA	FR	DE	HK	IT	JP	NL	ES	SE	CH	GB	US
Oct-12	3	3	6	5	2	1	13	6	2	2	5	13	39
Jan-13	3	3	6	5	2	1	14	5	2	2	5	12	39
Apr-13	3	2	6	5	2	1	14	5	2	2	5	12	40
Jul-13	3	3	7	6	2	1	10	6	2	2	6	13	40
Oct-13	3	2	6	6	2	1	10	6	2	2	5	13	42
Jan-14	3	2	7	6	2	2	12	6	2	2	6	12	39
Apr-14	3	3	6	6	2	2	11	7	2	2	5	12	40
Jul-14	3	3	6	5	2	1	9	8	2	2	5	11	42
Oct-14	3	3	5	5	2	1	10	7	2	2	5	10	45
Jan-15	3	3	5	5	2	1	10	8	2	2	4	10	45
Apr-15	3	3	5	5	2	1	10	7	2	2	4	10	45
Jul-15	2	3	5	5	2	1	10	7	2	2	5	10	46
Oct-15	3	3	5	5	2	1	10	6	2	2	5	10	47
Jan-16	3	3	5	5	2	1	9	7	2	2	4	10	48
Apr-16	3	3	5	5	2	1	9	7	2	2	5	9	49
Jul-16	3	3	5	5	2	1	9	7	2	2	5	9	48
Oct-16	3	3	5	5	2	1	9	6	2	2	4	9	49
Jan-17	3	3	5	5	2	1	9	7	2	2	4	9	49
Apr-17	3	3	5	5	2	1	9	7	2	2	4	9	48
Jul-17	3	3	5	5	2	1	9	7	2	2	4	9	48
Oct-17	3	3	5	5	2	1	10	7	2	2	4	9	49
Jan-18	3	3	5	5	2	1	9	7	2	2	4	9	48

Table 16. **Country allocation fixed income**: This table shows the cross-sectional average relative weights invested in the following countries for fixed income: Austria (AT), Belgium (BE), Denmark (DK), Finland (FI), France (FA), Germany (DE), Greece (GR), Ireland (IE), Italy (IT), Netherlands (NL), Norway (NO), Portugal (PO), Spain (ES), Sweden (SE), Switzerland (CH), and the United Kingdom (GB). The relative weights are in percent and add up to 100.

	Fixed income															
Date	AT	BE	DK	FI	FR	DE	GR	IE	IT	NL	NO	PO	ES	SE	CH	GB
Jan-06	2	3	1	1	16	18	3	1	10	32	1	0	4	1	0	6
Apr-06	2	3	2	1	17	17	2	1	10	31	0	0	6	1	0	5
Jul-06	3	3	3	0	16	19	3	1	10	29	0	1	6	2	0	5
Oct-06	3	3	3	1	17	19	4	1	10	27	1	0	5	1	0	6
Jan-07	3	3	4	1	15	18	4	1	11	25	0	1	6	1	0	8
Apr-07	3	3	5	1	14	18	4	2	12	24	1	1	6	1	0	6
Jul-07	4	3	4	1	16	16	4	2	11	24	1	1	6	1	0	7
Oct-07	2	3	1	1	18	18	3	3	12	23	1	1	6	1	0	8
Jan-08	2	3	2	0	17	18	4	3	13	22	1	0	6	1	0	8
Apr-08	3	3	2	0	17	18	4	3	13	20	1	0	6	1	0	8
Jul-08	2	3	2	1	16	17	4	4	13	20	1	1	6	1	0	10
Oct-08	2	3	2	0	17	18	5	3	14	19	1	1	5	1	0	8
Jan-09	3	4	1	1	18	18	4	3	15	12	1	1	6	1	0	12
Apr-09	3	3	1	1	18	18	4	3	14	13	1	1	6	1	0	12
Jul-09	3	3	2	1	18	16	4	3	15	14	1	1	6	1	0	11
Oct-09	3	3	2	1	18	16	4	3	14	14	1	1	6	1	0	11
Jan-10	3	3	1	1	18	17	4	3	16	13	1	1	6	1	0	10
Apr-10	3	3	2	1	19	18	4	3	14	13	1	1	6	2	0	10
Jul-10	4	4	2	2	18	19	3	3	14	13	1	1	6	2	0	9
Oct-10	4	3	2	2	18	20	3	2	12	13	1	1	6	1	2	9
Jan-11	4	3	1	2	18	21	2	2	11	15	1	1	6	1	0	10
Apr-11	4	3	1	2	19	21	4	2	10	16	1	1	6	1	0	9
Jul-11	4	3	1	2	20	21	3	2	9	16	1	1	6	2	0	9
Oct-11	4	3	1	3	19	23	2	2	7	19	1	1	5	2	0	9
Jan-12	4	3	1	2	18	26	2	1	7	19	1	0	6	2	0	9
Apr-12	4	3	1	2	18	26	1	1	6	20	1	0	4	2	0	8
Jul-12	4	3	1	2	18	27	0	1	6	20	1	0	3	2	1	9
Oct-12	4	2	1	3	18	28	0	1	6	21	1	0	3	2	1	8
Jan-13	4	3	1	3	18	28	0	1	6	20	1	0	4	2	1	8
Apr-13	4	3	1	3	18	26	0	2	6	20	1	0	4	2	1	9
Jul-13	5	3	1	3	18	26	0	2	6	21	1	0	4	2	1	8
Oct-13	4	3	1	3	18	27	0	2	5	21	1	0	4	2	1	8
Jan-14	5	3	1	3	18	26	0	2	6	21	1	0	5	2	1	8
Apr-14	5	3	1	3	19	26	0	2	6	21	1	0	4	1	1	7
Jul-14	5	3	1	3	19	25	0	1	6	21	1	0	5	1	1	7
Oct-14	5	3	1	4	18	26	0	1	6	21	1	0	4	1	1	7

Date	AT	BE	DK	FI	FR	DE	GR	IE	IT	NL	NO	PO	ES	SE	CH	GB
Jan-15	5	3	1	3	19	25	0	2	5	20	1	0	5	1	1	7
Apr-15	5	4	1	3	20	25	0	2	6	20	1	0	5	1	1	7
Jul-15	5	4	1	3	19	25	0	2	6	20	1	0	4	1	1	6
Oct-15	5	4	1	3	19	25	0	2	6	20	1	0	5	1	1	6
Jan-16	5	4	1	3	19	25	0	2	6	20	1	0	5	1	1	6
Apr-16	5	4	1	3	19	26	0	2	6	20	1	0	4	1	1	6
Jul-16	5	4	1	3	19	25	0	2	6	20	1	0	5	1	1	6
Oct-16	5	4	1	3	19	25	0	2	6	21	1	0	5	1	0	7
Jan-17	5	4	2	3	19	25	0	2	6	20	1	0	5	1	0	7
Apr-17	5	4	2	3	19	25	0	2	5	21	1	0	5	1	1	7
Jul-17	5	4	1	2	19	26	0	2	5	21	1	0	5	1	1	7
Oct-17	5	4	2	2	19	26	0	2	4	21	1	0	4	1	1	7
Jan-18	5	4	2	3	19	25	0	2	4	21	1	0	4	1	1	7

Table 17. **Country AUM fixed income *nominal value***: This table shows the *nominal* cross-sectional average AUM (in millions) invested in the following countries for fixed income: Austria (AT), Belgium (BE), Denmark (DK), Finland (FI), France (FA), Germany (DE), Greece (GR), Ireland (IE), Italy (IT), Netherlands (NL), Norway (NO), Portugal (PO), Spain (ES), Sweden (SE), Switzerland (CH), and the United Kingdom (GB).

Date	AT	BE	DK	FI	FR	DE	GR	IE	IT	NL	NO	PO	ES	SE	CH	GB
Apr-09	75	92	48	39	526	342	157	231	645	1018	28	74	508	41	2	451
Jul-09	86	96	52	35	873	374	255	324	1060	990	41	113	654	41	8	552
Oct-09	89	83	56	37	816	440	200	306	1056	954	36	87	571	36	0	467
Jan-10	104	106	36	46	952	576	239	330	1234	1000	45	174	744	41	22	476
Apr-10	105	108	41	48	1051	666	93	310	1197	1088	35	148	671	40	36	502
Jul-10	144	130	39	44	1067	680	128	239	1208	1131	33	110	688	40	36	469
Oct-10	147	131	33	44	1100	716	105	209	1269	1127	20	108	724	38	23	485
Jan-11	180	190	36	46	1365	779	256	213	1600	1100	24	137	892	36	11	574
Apr-11	182	215	29	48	1364	933	229	236	1664	1151	24	99	977	37	13	550
Jul-11	200	205	29	68	1504	966	253	222	1222	1250	25	80	989	39	13	513
Oct-11	207	173	44	87	1366	1161	259	191	1317	1300	52	53	1011	80	26	544
Jan-12	214	187	75	95	1605	1299	146	181	1373	1471	64	33	838	102	25	565
Apr-12	235	179	70	97	1638	1465	68	168	1250	1431	77	17	589	109	32	548
Jul-12	211	185	70	102	1926	1532	56	175	1186	1649	78	18	479	113	32	492
Oct-12	218	202	66	100	1881	1578	2	174	1209	1744	74	16	627	115	52	499
Jan-13	245	227	66	109	1898	1559	2	207	1381	1696	69	13	882	122	57	483
Apr-13	247	239	68	126	1946	1451	2	218	1469	1477	68	10	1009	124	104	468
Jul-13	245	231	76	126	2077	1417	2	201	1474	1421	70	11	1026	130	74	477
Oct-13	234	219	75	130	2074	1369	5	183	1442	1344	66	18	1170	122	62	448
Jan-14	256	272	75	149	2015	1353	4	185	1474	1333	69	33	1149	124	82	436
Apr-14	243	291	78	141	2063	1384	2	192	1507	1300	65	47	1065	123	74	456
Jul-14	245	322	89	138	2093	1433	3	202	1498	1316	61	53	1156	105	80	466
Oct-14	240	311	84	140	1951	1543	5	227	1378	1363	61	50	1196	102	66	514
Jan-15	246	377	77	141	2138	1582	2	248	1372	1364	62	74	1289	100	60	592
Apr-15	255	401	66	134	2207	1606	2	251	1428	1385	68	84	1202	100	70	609
Jul-15	256	439	72	143	2229	2689	3	248	1365	1406	66	74	1166	95	71	629
Oct-15	270	406	68	134	2062	1646	2	255	1225	1347	65	75	1037	97	87	683
Jan-16	241	383	82	125	1944	1524	2	270	1140	1333	67	67	961	102	80	741
Apr-16	239	381	81	134	1874	1423	2	275	1252	1333	65	54	932	95	81	800
Jul-16	230	376	91	123	1843	1395	1	3431	1266	1311	70	46	792	102	78	805
Oct-16	231	397	84	108	1813	1363	1	250	1114	1325	59	34	789	91	14	823
Jan-17	241	406	96	126	1865	1329	1	274	843	1382	76	30	860	112	17	835
Apr-17	220	421	95	122	1900	1302	1	268	887	1423	82	25	868	121	33	850
Jul-17	246	423	101	133	1947	1431	1	322	989	1515	82	33	814	133	39	856
Oct-17	236	355	99	122	1701	1329	2	304	890	1485	84	52	613	135	42	747
Jan-18	229	342	96	134	1628	1313	2	276	756	1447	94	55	583	127	47	710