I. Introduction

Liability-driven institutional investors substantially differ from mutual funds. Mutual funds are professionally managed investment funds that pool money from a heterogeneous group of investors with the aim of making returns through buying and selling securities. The investors are the shareholders of the mutual fund. A mutual fund operates with an 'asset-only' perspective and typically, but not exclusively, specialises in an asset class, market, or investment style. A liability-driven investor, by contrast, makes professional investment decisions from an 'asset-liability' perspective. The investments serve to finance future liabilities of the investor to its beneficiaries. Key liability-driven investors are pension funds, insurance companies and endowment funds. Their beneficiaries are often more homogeneous, for instance company employees that collectively save and invest for their retirement, or consumers that have a specific demand for insurance. Liability-driven investors generally have broad diversified investment portfolios, with equities, fixed income securities and less liquid assets such as private equity, real estate, and infrastructure.

Whereas many papers analyse mutual funds' investment strategies, e.g., Grinblatt et al. (1995), Brown and Goetzmann (1997), and Chan et al. (2002), so far, little is known about the investment strategies of liability-driven investors. Yet, liability-driven investors play a pivotal role in society as many beneficiaries depend on the investment performance of these investors. Understanding how liability-driven investors finance their future liabilities is important as this may have a substantial impact on beneficiaries' purchasing power. For instance, in the case of long-term investors such as pension funds, compounded returns have a huge impact on retirement income: 100 basis points lower annual returns over the accrual phase reduces retirement income by a quarter. Furthermore, beneficiaries often cannot freely choose their pension fund and there is little competition across pension funds.

We empirically study the investment strategies of liability-driven investors using proprietary data on occupational pension funds. Instead of assessing asset allocations, we study investment strategies more granularly by measuring factor exposures *within* equity and fixed income portfolios.

Measuring factor exposures, and thus investment strategies, requires data on holdings or returns at the asset class level. Our object of study are 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 2016, the AUM equaled approximately 1.3 trillion euros, and the Dutch pension system represented 54 percent of total assets of pension funds in the euro area, (OECD 2017). The proprietary data that we use are quarterly asset class returns over the period from 1999 to 2017, and return computations are based on the Global Investment Performance Standards (GIPS) as of 2010. Reporting requirements are mandatory and the data are therefore free from self-reporting biases.

Considering the broad diversified portfolios of pension funds, we use global factors to study investment strategies at the asset class level. The literature on global factors evolved substantially over the past decade and 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 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 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 differences in investment strategies, which, in turn, lead to differences in performance across pension funds. In Section V, we research pension fund's characteristics that drive heterogeneity in factor exposures following from our theoretical framework described in Section II. Motivated by the academic literature, we also study the effect 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 us with information about the extent to which pension funds change their investment strategies over time. In particular, we zoom in on exogenous events such as changes in pension fund regulations and the European sovereign debt crisis to study how these events impact investment strategies of pension funds.

We report the following key results. First, we show in Section IV that the average pension fund has a stock market beta lower than 1 and a fixed income market beta larger than 1. 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. Second, we find substantial heterogeneity in both equity and fixed income factor exposures across pension funds. On a total portfolio level, the contribution of all factors to overall expected returns is 2.26 percentage points higher for pension funds with the highest factor exposures compared to pension funds with the lowest.

In Section V we study the drivers of these factor exposures. First, we assess the impact of funding ratio, risk-aversion (proxied by the inverse of the required funding ratio), and liability duration (proxied by the ratio of retirees to total participants) on factor exposures that follow from our theoretical framework and make the following observations. First, we find no substantial relation between the funding ratio and equity factor exposures. By contrast, for fixed income we see that pension funds with a high funding ratio have less exposure to the 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 index. For fixed income, these pension funds have higher exposure to the investment grade fixed income market index, but lower aggregate exposure to the long-short factors. Third, pension funds with a high liability duration, i.e. a low fraction of retirees, do not differ in their equity exposures. For fixed income, a high liability duration implies a higher exposure to the investment grade market index, but lower exposure to 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 high liability durations have generally higher exposures to the investment grade fixed income market index, but lower exposure to the other factors. However, the negative exposures to some of the factors is inconsistent with our model and point to an inefficiency.

Next to the variables predicted by the model, and motivated by the academic literature, we also study pension funds size and asset manager. First, size, measured as assets under management, does not have an impact on the exposures to long-short factors. This observation means that, contrary to common belief, large pension funds are not constrained in implementing factor strategies. Second, for both equity and fixed income, asset managers do play a non-trivial role. The five most often contracted delegated asset managers amplify factor exposures. For instance, the exposure to the equity value factor may decrease with 0.05 or increase with 0.21 depending on the delegated asset manager, relative to an average value exposure of 0.04. For fixed income, the delegated asset manager may increase the exposure to value with 0.10 or 0.14, relative to the average value exposure of -0.23. Asset managers employed by pension funds 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.

Finally, in Section VI, we observe that the time variations in the conditional long-short factor exposures for equities is minor. However, the time variation in conditional long-short factor exposures for fixed income is much larger. The average long-short factor exposures can get as low as −0.9 (for the value factor exposure in 2012) and as high as 1 (for the carry and momentum factor exposures in 2011). In Section V we also show that the large changes in factor exposures for fixed income are due to active portfolio repositioning. For instance, pension funds increased their exposures to vulnerable countries (Greece, Ireland, Italy, Portugal, and Spain) during the aftermath of the financial crisis. However, towards the end of 2010, they substantially decreased their holdings in vulnerable countries. For instance, the average allocation to Greece went down from approximately 250 million in 2011 to only 2 million by the start of 2013 and for Portugal the average allocation of 110 million went down to approximately 12 million (nominal values).

Literature review

Our paper contributes to the literature on investment behavior in a regulated environment. Rauh (2009) shows that underfunded corporate 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) that underfunded pension funds take less risk within an asset class. We find that underfunded pension funds, within their fixed income portfolio, invest more in investment-grade bonds and take less credit risk. This 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 in a pension funds board may therefore push for risk reduction to avoid this risk shifting. Andonov et al. (2017) find that US public pension funds increase their risk-taking in financial markets when the interest rates 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. This incentive is created through the US GAAP accounting standards. We add to this work by analysing pension fund investment behavior in a regulatory environment in which pension funds are not free to choose their own discount rate. The incentive found by Andonov et al. (2017) is consequently not observed in our data. Greenwood and Vissing-Jorgensen (2018) show that regulatory changes in the discount curve, which are used by insurance companies and pension funds to value their liabilities, affect the yield curve due to a shock in demand for long-term bonds from these investors. Our results also support the view that regulation shapes pension funds' investment behavior, in particular within fixed income portfolios. Our results show pension funds' preference for safe long-term bonds as well as securities denominated in euros.

Our work also relates to the investment behavior of long-term investors during periods of low interest rates. Next to Andonov et al. (2017), also Lu et al. (2019) 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 increased their exposure to the investment grade fixed income index, while slightly lowering their exposure to credit risk. A logical explanation for this is that regulation in the Netherlands does not allow pension funds to increase risk-taking when they are underfunded (Section VI), but this limitation does not hold for US public pension funds. Our results are more in line with investment behavior of German insurance companies, as shown by Domanski et al. (2017), that demand more safe long-term bonds when interest rates are low ('hunt for duration').

Our paper also contributes to the literature that assesses the impact 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 findings support this because we find many factor exposures to be negative on average. We conjecture that regulation is a driving force for preferences for assets in the short leg of the anomaly. For instance, during the euro sovereign debt crisis pension funds exposure 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 factor exposures. 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 optimal factor exposures and explain heterogeneity across pension funds. First, we derive optimal portfolio weights using a mean-variance investor that optimizes its surplus, i.e. 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 and to include borrowing and short-sale constraints that are typically applicable to liability-driven investors. Second, we transform the optimal portfolio weights into optimal factor exposures.

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

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

where r_t^h is the discount rate as observed today t for maturity $t+h$. Discount rates vary widely across jurisdictions. For instance, under US GAAP public pension funds discount their liabilities at the expected rate of return on the assets (Andonov et al. 2017). US corporate pension funds, by contrast, 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. Regulations introduced in 2007, however, requires 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).[1] Finance theory implies that risk-free market interest rates are indeed the applicable discount for guaranteed pension benefits to exclude arbitrage. The value of the liabilities at time $t+1$ can be defined as follows:

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

where r^L_{t+1} is the liability return, which in turn is approximated by the return on a set of risk-free bonds r^b_{t+1} times ψ, the duration of liabilities over the duration of the set of bonds. The value of ψ is typically larger than 1 as the duration of 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 wealth of the pension fund evolves as follows:

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

where w_t is a vector of portfolio weights that the pension fund chooses at time t and r_{t+1} a vector of returns from t to $t+1$. Following Sharpe and Tint (1990), 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 normalise the surplus by diving assets and liabilities by the value of assets to get the following optimization problem:

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

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

subject to

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

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

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

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

with

$$\begin{aligned} w_{i,t}^* &\geq 0, \\ \delta_i &\geq 0, \\ \delta_i w_{i,t}^* &= 0 \ \ \forall i, \end{aligned} \tag{8}$$

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

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

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 speculative demand decreases if hedging demand increases, and vice versa.

In our empirical analysis, we measure factor exposures instead of portfolio weights. We can transform the optimal portfolio weights in (7) into factor exposures as follows. Assume that the assets pension funds can invest in are K factors with return r^k. The portfolio return under this specification equals $r^P_{t+1} = w_t' r_{t+1}$. The exposure of the portfolio return to 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, this can be further decomposed to:

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

where $r^{k,L}$ is the return on the 'long-leg' of the factor and $r^{k,S}$ the return on the 'short-leg' of the factor. Plugging in the portfolio return in (10), we have that:

$$\beta^k = w^k, \tag{12}$$

where $w^k = w^{k,L} - w^{k,S}$ for the long-short factors by (11). The optimal weights in (7) can therefore also be interpreted as factor exposures. Although the pension fund cannot go short in assets, it may have negative exposures to a long-short factor. A positive factor exposure results from a higher demand for the long-leg compared to the demand for the short-leg of the factor, 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 a very high 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 ($\text{Cov}_t(r^L_{t+1}, r_{t+1}) > 0$), will lead to a positive factor demand from a liability hedging perspective.
2. A longer liability duration, i.e. a higher ψ, implies 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 if the borrowing constraint is binding. This implies that demand for factors uncorrelated with the liability return decreases if hedging demand increases.

B. *Testable implications*

This section 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 proxy for return on the set of bonds r^b_{t+1}.[2] Further we use the following factors for fixed income:

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

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 set of bonds ψ are all pension fund specific. We have data on 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 have a higher required funding ratio.[3] We also do not have data on liability durations of pension funds over a long enough period, but we have data on the fraction of retirees relative to total participants. The liability duration is inversely related to the ratio of retirees to total participants: a high ratio of retirees implies a low liability duration, i.e. a low ψ.

1. **Liability structure**

   Because pension funds discount benefits using the term structure of market interest rates (as of 2007), we predict an average exposure to the 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)[4], we predict zero or 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 index 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

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

[4]The solution for the speculative demand using Table 2 and 3 is that all exposures are strictly positive irrespective of the value of γ.

to factors other than the investment grade fixed income market index, and vice versa. Risk aversion is approximated through the inverse of the 'required funding ratios'.

- *Liability duration*

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

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 report the overall portfolio return, as well as the returns from the equity and the fixed income portfolios separately. 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 times 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 reduces 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 that are at least 24 quarters 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. We compute the standard deviation using the law of total variance: $\sigma(r) = \sqrt{\mathbb{E}_i(\text{Var}[r]) + \text{Var}_i(\mathbb{E}[r])}$. The negative skewness indicates the equity return series has relatively strong negative values. The kurtosis in excess of 3 demonstrates fat tails. The mean excess return on fixed income is 3.87 percent per year with a standard deviation of 7.98 percent. The relatively high excess return on fixed income illustrates the significant drop in market interest rates over the sample period. The high kurtosis indicates a relatively peaked distribution 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 reports the value-weighted statistics for returns and asset allocations. The value-weighted mean excess return for equities equals 4.79 and for fixed income 3.71 percent annually.

Table 2 also presents the average strategic allocations to equity and fixed income, the duration of the fixed income portfolio, the funding ratio, the required funding ratio, and the ratio to retirees. Pension funds invest on average 31 percent in equities and 59 percent in fixed income. The average duration of the fixed income portfolio equals 8.2 years, with a substantial standard deviation of 8.7 years, indicating that 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 115 percent. The ratio of retirees equals 35.75 percent on average, indicating that over one-third of the participants in the pension fund 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).[5] 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 factor return, momentum factor return, carry factor return, and low beta factor return to explain 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

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

although we do not have data on the exposure to the euro area prior to 2007, we expect this fraction to be higher. For instance, Berk and van Binsbergen (2015) show that the fraction of mutual funds investing 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 index, we use the quarterly MSCI World Total Return Index in euros; for the European market index, we use the Euro Stoxx 50 Total Return Index from Bloomberg in euros.[6]

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 equity 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 factor returns are all monthly factor returns. To match with the pension funds' return cycle, we convert the monthly returns to quarter returns by means of compounding. We assume pension funds fully hedge currency exposures and convert all dollar returns to euros.[7] 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 into annual factor returns.

Panel B of Table 2 contains the summary statistics for the factors returns. Within

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

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

equities, the low beta factor has the highest annualized return (11.03 percent), while value has the lowest annualized return (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 that 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 invest, on average, 87 percent of the fixed income portfolio in the euro area. Again, we expect this fraction to be even larger prior to 2007. A currency bias/preference for euro fixed income is logical because pension funds' liabilities are also denominated in euros and fixed income is mainly used for liability hedging purposes. We therefore use European factors for fixed income, as opposed to global factors for equities. We use the Bloomberg Barclays Euro Aggregate Bond Index and the Bloomberg Barclays Euro High Yield Index in euros as the market and credit indexes respectively.[8] Table 2 shows both equally and value-weighted excess fixed income returns of pension funds are above the excess return of the 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 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

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

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 period. Appendix A 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 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 0.56 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 low beta (4.71), momentum (4.54), and carry (4.52). 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 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 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:

$$r_{it}^{a} - r_{ft} = \alpha_i^a + \beta_i^{a'} f_t^a + \epsilon_{it}^a, \quad \text{for} \quad i = 1, ..., N, \tag{13}$$

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 a zero-mean, normally distributed 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 market fixed income 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 regressions in Equation (13).

[Place Table 4 about here]

B. Prior factor exposures

The estimated factor exposures using the time-series OLS regressions in Equation (13) 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. As we are interested in 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 cross-sectional variation in the parameters. We specify the random-coefficients model as follows:

$$
\begin{aligned}
r_{it} - r_{ft} &= \alpha_i + \beta_i' f_t + \epsilon_{it} \\
&= \alpha + \beta' f_t + v_i' f_t + u_i + \epsilon_{it},
\end{aligned} \tag{14}
$$

in which v_i is a vector of length L that captures all the random-effect coefficients, and ϵ_{it} a zero mean, normally distributed idiosyncratic error term with variance σ_i. We assume furthermore 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 of 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 (13) towards the prior to obtain posterior betas. The prior betas are now defined as:

$$\beta_i^k \sim N(\hat{\beta}^k, \hat{\sigma}^2_{\beta^k}) \quad \text{for} \quad k = 1, ..., K \quad \text{and} \quad i = 1, ..., N, \tag{15}$$

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 (14). Table 5 shows the results of the random-coefficients 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 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 coefficients estimates are 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:

$$\tilde{\beta}_i^k = \frac{\hat{\beta}_i^k / se(\beta_i^k)^2 + \hat{\beta}^k / \hat{\sigma}^2_{\beta^k}}{1/se(\beta_i^k)^2 + 1/\hat{\sigma}^2_{\beta^k}} \quad \text{for} \quad k = 1, ..., K \quad \text{and} \quad i = 1, ..., N \tag{16}$$

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

in which $\hat{\beta}_i^k$ is the estimated exposure to factor k from the time-series OLS regressions presented in Equation (13) for pension fund i, and $se(\beta_i^k)$ is the corresponding standard error. Equation (16) implies 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, which indicates that 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 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 of 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 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 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 time-series regressions in Table 4 is due to measurement error, although 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 towards the mean, and the standard deviations obtained from the time-series regressions in Table 4 are almost all due to measurement error.

[Place Table 6 about here]

D. Heterogeneity in expected returns

Variation in factor exposures has consequences for expected returns, and thus on expected performance differences across institutional investors. To determine these differences, we compute for each pension fund the contribution of the market and the long-short factor exposures to expected returns. In this subsection, we use posterior betas obtained from Equation (16). The contribution from the market exposure to the expected return is computed as:

$$\mathbb{E}(r_i^M) = \tilde{\beta}_i^{M\prime} \lambda^M \quad \text{for} \quad i = 1, ..., N, \tag{18}$$

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 historical average returns. We compute the contribution of long-short factor exposures to expected returns similarly:

$$\mathbb{E}(r_i^F) = \mathbb{E}(r_i - r_i^M) = \sum_{k=3}^{K} \tilde{\beta}_i^k \lambda^k \quad \text{for} \quad i = 1, ..., N. \tag{19}$$

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

The empirical distributions of Equations (18) and (19) delivers the variation in expected returns due to the differences in factor exposures. For equities, Table 7 shows that taking both market and long-short factors together, the overall contribution of factor exposures varies between 2.27 and 6.53 percent. Pension funds with the highest market exposure have an expected return on the market that is equal to 4.70 percent, whereas the expected return for pension funds with the lowest market exposure equals 4.05 percent. 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 percent at the highest and −1.11 percent 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 percent. The variation in the contributions of market exposures are larger than for equities and vary between 2.07 and 4.04 percent. Again we attribute this finding to the differences in durations that pension funds chose in their fixed income portfolios. 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 expected returns equals 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 percent for the entire portfolio, and the contribution of long-short factor exposures has values that vary between −0.41 and 0.65 percent. For the long-short factors only, pension funds with the highest total long-short factor exposures have a 1.06 percent higher expected return on the entire portfolio.

In sum, heterogeneity in factor exposures matters for heterogeneity in expected returns. The heterogeneity in expected returns is primarily driven by long-short factors for equities, but by the market for fixed income.

[Place Table 7 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 factor exposures. We first calculate the average return of each pension fund per asset class using Equation (16):

$$\tilde{\mu}_i = \tilde{\alpha}_i + \tilde{\beta}_i' \lambda_i \quad \text{for} \quad i = 1, ..., N, \tag{20}$$

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

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

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

Table 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, which explains 8.14 percent of the variation in average returns. Value explains 5.46, carry 5.74, and momentum 0.69 percent in average returns. The total exposure to long-short factors thus explains 20.03 percent of 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.[9]

For fixed income, the excess European market index explains 91.77 percent of the variation in average returns and the high yield index 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 realized average returns. Thus, similar to equities, we find that long-short factors explain approximately 28.35 percent in the absolute value of the cross-sectional differences in average fixed income returns. Again, this is consistent with the highest heterogeneity in market factor exposures found for fixed income.

[Place Table 8 about here]

V. What drives factor exposures?

In the previous sections we have seen that some factor exposures are on average negative, but substantial heterogeneity in factor exposures across pension funds exists. In this section we aim to understand the drivers behind these factor exposures by testing the testable 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, size, and asset managers.

A. Liability structure

Do pension funds 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 show, 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.

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

Liability returns are not only affected by interest rates, but also by indexation of benefits or benefit reductions, if any. Other components such as changes in survival probability or participants that transfer their pension benefits to another pension fund also affect liability returns, although these effects are generally of second order. To formally test the determinants of liability returns, we regress liability returns on all factors:

$$r_{it}^{L} - r_{ft} = \alpha_i + \beta_i^{'} f_t + \epsilon_{it}, \quad \text{for} \quad i = 1, ..., N, \tag{22}$$

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:

$$r_{t+1}^{L} = \frac{L_{t+1} - L_t - I_t}{L_t + \frac{1}{2} I_t} \tag{23}$$

Liability returns contain substantial noise for mainly two reasons. First, liability returns are affected by non market factors such as benefit transfers between pension funds. Second, we have to make an assumption on the timing of cash flows during the quarter. Therefore, to reduce measurement error, we estimate (22) for pension funds that are in the sample from 2007Q1 to 2017Q4 only (76 pension funds).[10] The results are in Table (9).

The liability return is primarily driven by the investment grade fixed income market index, with an average exposure equal to 2.10. This exposure is consistent with liability durations of pension funds. The average liability duration of pension funds equals approximately 17 years (Broeders et al. 2020), whereas the average duration of a typical fixed income market index equals only roughly 7 years. The exposure to all the other factors are not statistically significant, except borderline significant for carry. Given that we estimate 12 coefficients,

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

we expect 1 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 fixed income market index. However, the exposure of the liability return to long-short factors does not seem to explain the average negative exposures to value and carry.

B. *Pension funds' characteristics*

In this section we analyze the impact of pension funds' characteristics on factor exposures. We estimate the impact of the funding ratio, the risk-aversion (proxied by the inverse of the required funding ratio), the liability duration (proxied by the ratio of retirees to total participants), 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 including funding ratio, the inverse of the required funding ratio, ratio of retirees to total participants, size, and asset managers' quarter fixed effects interacted with the factor returns:

$$\begin{aligned} r_{it}^{e} &= \beta_0' f_t + \beta_1' f_t \times \mathrm{FR}_{it} + \beta_2' f_t \times 1/\mathrm{RFR}_{it-1} + \beta_3' f_t \times \mathrm{RR}_{it-1} + +\beta_4' f_t \times \mathrm{AUM}_{it-1} \\ &+ \beta_5' (f_t \times AM_{it-1}') \iota_5 + \epsilon_{it}, \end{aligned} \tag{24}$$

in which FR_{it-1} is the funding ratio of pension fund i at time $t-1$ relative to the average funding ratio of all pension funds at time $t-1$, $1/\mathrm{RFR}_{it-1}$ is the inverse of the required funding ratio of pension fund i at time $t-1$ relative to the average funding ratio of all pension funds at time t, RR_{it-1} is the ratio of retirees to total participants for pension fund i at time $t-1$ relative to the average ratio of retirees to total participants for all pension funds at time $t-1$, AUM_{it-1} is the AUM for pension fund i at time $t-1$ for the corresponding asset class relative to the average AUM of all pension funds at time $t-1$, AM_{it-1} is a vector

C. Implied beliefs on expected factor returns

The high heterogeneity in the expected returns shown in Subsection D also indicates 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 their expected factor returns. To do so, we apply the method as described in Shumway et al. (2011). In their work, ith fund manager's implied beliefs about expected returns, $\hat{\mu}_i$, are derived as follows[13]:

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

in which Σ_i is the variance-covariance matrix of factor returns, which is estimated using historical return data and is therefore similar across managers ($\Sigma_i = \Sigma$), w_i the portfolio weights, and q_i the benchmark portfolio weights. The true beliefs are an affine function of implied beliefs (Shumway et al. 2011):

$$\mu_i \approx \gamma_i \delta_i \Sigma_i(w_i - q_i) - \lambda \mathbf{1} \qquad \text{for} \qquad i = 1, ..., N, \tag{26}$$

where 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 $\delta_i = \tau^{-1} + \tau_i^{-1}$: in which 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. We refrain from private signals and set $\tau_i = 0$.

Because we cannot observe all parameters required to derive true beliefs, we assume reasonable parameter values to get estimates of implied beliefs on expected factor returns.

[13] In solving implied beliefs about expected returns, Shumway et al. (2011) assume that fund managers choose portfolio weights such that they maximize expected returns over a benchmark while minimizing the tracking error volatility.

The results that follow should therefore be interpreted as approximations of true beliefs, where we are particularly interested in the order of magnitude of differences in expected returns across factors.

We assume that all pension funds have the same risk aversion of $\gamma_i = 5$ and that the short-sale constraint of pension funds is not binding which means that $\lambda = 0$. We also assume pension funds have the same overall precision of the prior equal to $\tau = 1$. Together with the with the assumption of no private signals ($\tau_i = 0$) we have $\delta_i = 1$. A precision of the prior equal to $\tau = 1$ means that pension funds have a prior $p(\mu_0)$ that is normally distributed with mean μ and variance-covariance Σ, that are, for instance, based on historical returns:

$$p(\mu_0) \sim N(\mu, \Sigma). \tag{27}$$

We estimate this mean and the variance-covariance matrix using the factor returns over the full sample. We derive portfolio weights from betas in the following way. Assuming there is a benchmark with return r_t^B, we can write the portfolio return for pension fund i as a function of the benchmark return and factor exposures as follows:

$$r_{it}^P = r_t^B + w_i' f_t \qquad \text{for} \qquad i = 1, ..., N, \tag{28}$$

in which w_i are the factor weights for pension fund i, and f_t are the factor returns. The portfolio weights are unconstrained because the long-short factor portfolios are zero-cost portfolios. A pension fund's factor exposures are derived from regressing portfolio returns relative to the benchmark returns on factor returns:

$$r_{it}^P - r_t^B = \alpha_i + \beta_i' f_t + \epsilon_{it} \qquad \text{for} \qquad i = 1, ..., N, \tag{29}$$

in which

$$\hat{\beta}_i = (f_t' f_t)^{-1} f_t' (r_{it}^P - r_t^B) = (f_t' f_t)^{-1} f_t' (w_i' f_t) = w_i. \tag{30}$$

Equation (30) shows that the estimated factor exposures are equal to factor weights. In estimating (29), we again correct the estimated factor exposures for measurement errors by using the Vasicek adjustment as described before.

For the benchmark returns, we use the MSCI World Index for equities and the Bloomberg Barclays Euro Aggregate Bond Index for fixed income. For the benchmark weights q_i, we assume zero weights for all the long-short factors. These weights corresponds to a passive investor who follows the benchmark exactly.

Table 12 shows the results for the annualized implied beliefs (Equation 26) on expected factor returns, conditional on all pension funds having the same risk aversion and the same informedness. For equities, a median pension fund has positive implied beliefs about value and low beta and negative implied beliefs about momentum and carry. The median implied belief for the value factor equals 2.25 percent, and this equals −2.22 percent for momentum, −1.09 for carry, and 2.16 for low beta. This implies pension funds on average expect 4 percent 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 0.94 percent, whereas pension funds with the most optimistic views expect a positive return of 5.61 percent.

For fixed income, the median implied beliefs on the value factor equal −1.61, 1.03 for momentum, −0.93 for carry, and 1.55 for low beta. The largest heterogeneity in implied beliefs on expected returns exists for low beta in which pension funds with the most pessimistic views on low beta expect a negative return of 0.11 percent, while pension funds with the most optimistic views expect a positive return of 3.58 percent.

VI. Conditional factor exposures

In the previous sections we analyzed the unconditional factor exposures. Factor exposures may change substantially over time and thereby have a significant impact on portfolio returns and risk. Therefore, in this section we estimate conditional factor exposures and estimate their impacts on portfolio returns and risks. We take the following two approaches. First, we estimate rolling factor exposures. Second, we analyse how factor exposures respond to external events that might be relevant to pension fund investing. Third, we show that changes in factor exposures for are due to active portfolio repositioning.

A. Rolling factor exposures

We estimate rolling factor exposures by using overlapping window regressions. We use an estimation window of 20 quarters and 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 2 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 conditional factor exposures for equities is only minor. Factor exposures within 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 -0.9 (for the value factor exposure in 2012) and as high as 1 (for the carry and momentum factor exposures in 2011).

Although the purpose of this paper is not to quantify changes in risk and return characteristics of the factors over time, we argue that the time variations we observe for fixed income are much larger than our theoretical framework would predict. Because the funding ratio changes over time, we expect some variation in factor exposures over time. This should however be mitigated by the fact that the standard deviation of the funding ratio equals 0.16 only and that the risk aversion parameter γ is fairly stable over time. To rationalize the large swings in fixed income factor exposures, the return characteristics of the factors should be highly time varying, which we think is unlikely given the robust performance of the factors.

[Place Figure 2 about here]

The large variation in fixed income factor exposures is important from a risk management perspective, as it critically affects portfolio risk. In order to show this, we compute the portfolio risk for equity and fixed income portfolios for every $t = w, ..., T$ by taking the square root of the variance of excess returns, as presented in Equation (13):

$$\hat{\sigma}(r_{it} - r_{ft}) = \sqrt{\hat{\beta}_t{}' \widehat{\Sigma}_t \hat{\beta}_t}, \tag{31}$$

in which $\widehat{\Sigma}_t$ is the variance-covariance matrix of the factor returns estimated over the window $[t - w + 1, t]$, and $\hat{\beta}_t$ is the cross-sectional average factor exposure estimated over the same window. We compare portfolio risk to the risk of a portfolio with only market factor exposures. This is equal to Equation (31) with all long-short factors exposures forced to zero.

Figure 3 shows the results for both equity and fixed income portfolios. First, it shows that the equity portfolio risk closely tracks the market risk. Factor exposures do not materially change portfolio risk. Second, equity portfolio risk declines over time. However, this is primarily due to a decrease in market risk over the sample period. For fixed income we observe the opposite. Fixed-income portfolio risk initially equals the market risk, but starts to deviate significantly after 2009. This deviation shows that the large level of and variation in long-short factor exposures increases risk relative to the market.

[Place Figure 3 about here]

Next we look at the decomposition of returns. How much do average factor exposures in combination with factor returns contribute to average portfolio returns? Figure 4 shows how the cross-sectional average factor exposures contribute to 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 pension funds in the sample minus the cross-sectional average lagged factor exposures times the realized returns on the factors. 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, particularly during the 2010-2015 period. For instance, during the period of 2012-2014, the negative exposure to value has often contributed negatively to average returns in the 2012-2014 period.

[Place Figure 4 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 will 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 legislator in the Netherlands introduced risk-based regulation as of the start of 2007. Key elements of this regulation include the prudent person principle, marked-to-market valuation of both assets and liabilities, funding requirements and recovery plans. Dutch pension funds do not face any quantitative investment restrictions, but they have to invest according to the prudent person principle outlined in the Pension Act.[14] This regulation means that pension funds should invest in the best interest of the participants. 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 ratio of about 104.2 percent.[15] The required funding rate, in contrast, is based on a pension fund's risk profile, and 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 120 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 of accrued benefits. In case of a funding shortfall, pension funds are however not allowed to increase the risk profile of their investment portfolio to gamble for resurrection. 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 legislator changed this regulation. Under the new regulation, recovery periods are a maximum of 10 years, independent of the funding requirement. This time frame allows pension funds to better smooth the impact of negative shocks over time. The change in recovery plan dynamics has had effects on pension fund investment and risk management.[16]

Figure 2 displays vertical lines that indicate the four events. Equity factor exposures only change slightly after the events. We observe a minor drop in the average exposure to

[14] www.wetten.overheid.nl/BWBR0020809

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

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

the MSCI World Index and a slight increase for the Euro Stoxx 50 Index 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 to the global market index, and a decrease to the European market index 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 investing more in bonds with long durations (or using interest rate swaps, but this part we do not observe in our data). The exposure to the market really took off around the euro sovereign debt crisis. Over the period 2003 to 2015, exposure to the market index increase 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 is a substantial increase to 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 already happened in 2010. The euro sovereign debt crisis has 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, that affect factor exposures dramatically. In the next section, we show that these variations in factor exposures are active choices by pension funds.

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 of Altavilla et al. (2016).[17] The triple-A rated country index is constructed as the equally weighted return on 10-year zero-coupon bonds for the following eight countries: Austria, Denmark, Finland, Germany, Netherlands, Norway, Sweden, and Switzerland.

Figure 5 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 an similar increase in investments to vulnerable countries from March to December 2010 for eurozone banks, to benefit from carry trades. 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. Regulation plays a key role in the early retraction of sovereign bond investments from vulnerable countries by Dutch pension funds compared to eurozone banks. Opposed to eurozone banks, Dutch pension funds are not allowed to assign zero-risk weights to non triple-A rated sovereign bonds. Government bonds from countries with lower ratings get higher risk weights.[18] Third, the exposure to the triple-A rated index increased significantly as of the peak of the euro sovereign debt crisis, which confirms flight-to-quality behavior (Acharya and Steffen 2015). Fourth, the exposure to the vulnerable country index

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

[18] www.toezicht.dnb.nl/2/50-202270.jsp

and the triple-A rated index move in opposite directions prior to the peak of the euro crisis. This movement confirms that pension funds actively change their country allocations, which again influence factor exposures.

As additional evidence for active reallocation across countries we also analyze country holdings over the period 2006Q1-2017Q4 for a sample of 42 pension funds that mandatory report their country holdings. For fixed income, we have country allocations both in market values and also in nominal values as of 2009Q1. Figure 6 summarizes the findings and shows the fraction invested in triple-A rated and vulnerable countries over time, both in market value as well as in nominal values, that are available as of 2009Q1. Nominal values are useful, as these are unaffected by prices. We compare the findings to Figure 5. The country allocation also confirms that pension funds increased their allocation to vulnerable countries until 2010, and then sharply reduced their allocation, whereas we observe the opposite effects for the triple-A countries. Additionally, Table 14 in the Internet Appendix C shows the fraction of fixed income invested in the thirteen countries that we analyze using market values, whereas Table 16 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 in Greece went down from approximately 250 million in 2011 to only 2 million by the start of 2013 and in Portugal the average allocation of 110 million went down to approximately 12 million (nominal values).

Table 15 in Internet Appendix C 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, UK, and US). We the exception of a sharp increase in the allocation to Japan in 2012, a sharp drop in the allocation to 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. Although to a smaller extent, the effects of active reallocation across countries is therefore also visible here.

VII. Conclusion

In this paper, we provide insight into the investment strategies of a large group of liability-driven investors that represents a large fraction of the European market for pension funds' assets. Studying factor exposures is key to understanding the heterogeneity in performance and investment strategies of liability-driven institutional investors. We report the following main results. In the first part, we show that the average pension fund has a stock market beta lower than 1 and a fixed income market beta larger than 1. 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. Second, we find substantial heterogeneity in both equity and fixed income factor exposures across pension funds.

In the next part of the paper we relate pension fund characteristics to explain differences in factor exposures that result from our theoretical framework. Overall, our findings are consistent with the predictions of our model: pension funds with a low funding ratio, high risk-aversion, and a high liability duration have generally higher exposures to the investment grade fixed income market index, but lower exposure to the other factors. However, the negative exposures to some of the factors is inconsistent with our model and point to an inefficiency. Moreover, size, measured as assets under management, does not have an impact on the exposure to long-short factors. Finally, for both equity and fixed income factor exposures, external asset managers play a non-trivial role, in which the effects are positive for some factors and negative for others.

In the final part, we observe that the time variation in the conditional long-short factor exposures for equities is minor. However, the time variation in conditional long-short factor exposures for fixed income is much larger. The average long-short factor exposures can get as low as -0.9 (for the value factor exposure in 2012) and as high as 1 (for the carry and momentum factor exposures in 2011). We show that the large changes in factor exposures for fixed income are due to active portfolio repositioning.

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. We suggest, consequently, 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 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 an monthly basis from 1994 to 2017. We complement missing data points prior to 1998 with zero coupon bond yields from Jonathan Wright's web-page for Norway, Sweden, Switzerland, and the UK. We use the Libor counterpart in each country as a proxy for the risk-free rate. The corresponding Bloomberg ticker numbers are listed in Table (13) in the Internet Appendix A. All included countries had investment-grade credit ratings over the entire sample period by Fitch, Moody's, and Standard & Poor's.

We start with 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:

$$P_{i,t}^{\tau,syn} = \frac{1}{1+r_{i,t}^f}\frac{1}{(1+y_{i,t})^T}, \tag{32}$$

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:

$$P_{i,t+1}^{\tau-1,syn} = \frac{1}{(1+y_{i,t+\tau})^{T-\tau}}, \tag{33}$$

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

$$r_{i,t}^{syn} = \Big(\frac{(1+r_{i,t}^f)(1+y_{i,t})^T}{(1+y_{i,t+\tau})^{T-\tau}} - 1\Big) \times \Big(1 + \frac{e_{i,t+1} - e_{i,t}}{e_{i,t}}\Big) \tag{34}$$

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, or momentum, or 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:

$$w_{it}^S = c_t(\text{rank}(S_{it}) - \sum_{i=1}^{J} \text{rank}(S_{it})/J), \quad \text{where } S \in (\text{value, momentum, carry, low beta}). \tag{35}$$

The weights across all securities sum to zero, representing 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 bu skip the most recent month. The signal for carry is defined as in Koijen et al. (2018):

$$C_{it} = \frac{(1 + y_{i,t}^{T})^{T}}{(1 + r_{i,t}^{f})(1 + y_{i,t}^{T-\tau})^{T-\tau}}. \tag{36}$$

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

$$\hat{\beta}_i = \hat{\rho}\frac{\hat{\sigma}_i}{\hat{\sigma}_m}, \tag{37}$$

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 one and five-year windows respectively. The market is defined as the average return of all bonds in our sample. To reduce the impact of outliers, we follow Frazzini and Pedersen (2014) and shrink the time series estimate of beta to one: $\tilde{\beta}_i = 0.6 \times \hat{\beta}_i + 0.4 \times 1$.

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

$$r_t^S = \sum_{i=1}^{J} w_{it-1}^S r_{it}^{syn}, \quad \text{where } S \in (\text{value, momentum, carry}). \tag{38}$$

The factor return for low beta is constructed as:

$$r_t^{\mathrm{S}} = \frac{1}{\beta_{t-1}^L}(r_t^L - r_t^f) - \frac{1}{\beta_{t-1}^H}(r_t^H - r_t^f), \quad \text{where } S \in (\text{low beta}), \tag{39}$$

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

References

Acharya, V. and S. Steffen (2015): "The "Greatest" Carry Trade Ever? Understanding eurozone bank risks," *Journal of Financial Economics*, 115, 215–236.

Altavilla, C., M. Pagano, and S. Simonelli (2016): "Bank Exposures and Sovereign Stress Transmission," European Systemic Risk Board Working Paper 11.

Andonov, A., R. Bauer, and M. Cremers (2017): "Pension Fund Asset Allocation and Liability Discount Rates," *The Review of Financial Studies*, 30, 2555–2595.

Asness, C. S., T. J. Moskowitz, and L. H. Pedersen (2013): "Value and Momentum Everywhere," *The Journal of Finance*, 68, 929–985.

Berk, J. and J. van Binsbergen (2015): "Measuring Skill in the Mutual Fund Industry," *Journal of Financial Economics*, 118, 1–20.

Binsbergen, J., M. Brandt, and R. Koijen (2008): "Optimal Decentralized Investment Management," *The Journal of Finance*, 63, 1849–1895.

Blake, D., A. Rossi, A. Timmermann, I. Tonks, and R. Wermers (2013): "Decentralized Investment Management: Evidence from the Pension Fund Industry," *The Journal of Finance*, 68, 1133–1178.

Broeders, D. and A. Chen (2012): "Pension Benefit Security: A Comparison of Solvency Requirements, a Pension Guarantee Fund, and Sponsor Support," *Journal of Risk and Insurance*, 80, 239–272.

Broeders, D., K. Jansen, and B. Werker (2020): "Pension Fund's Illiquid Assets Allocation under Liquidity and Capital Constraints," *Journal of Pension Economics and Finance*, forthcoming.

Brown, S. and W. Goetzmann (1997): "Mutual fund styles," *Journal of Financial Economics*, 43, 373–399.

Chan, L., H. Chen, and J. Lakonishok (2002): "On Mutual Fund Investment Styles," *The Review of Financial Studies*, 15, 1407–1437.

Cosemans, M., R. Frehen, P. Schotman, and R. Bauer (2016): "Estimating Security Betas using Prior Information Based on Firm Fundamentals," *The Review of Financial Studies*, 29, 1072–1112.

Coval, J. and E. Stafford (2007): "Asset Fire Sales (and Purchases) in Equity Markets," *Journal of Financial Economics*, 86, 479–512.

Dasgupta, A., A. Prat, and M. Verardo (2011): "Institutional Trade Persistence and Long-Term Equity Returns," *The Journal of Finance*, 66, 635–653.

de Bondt, W. and R. Thaler (1985): "Does the Stock Market Overreact?" *The Journal of Finance*, 40, 793–805.

Domanski, D., H. Shin, and V. Sushko (2017): "The Hunt for Duration: Not Waving but Drowning?" *IMF Economic Review*, 65, 113–153.

Easley, D. and M. O'Hara (1987): "Price, Trade Size, and Information in Securities Markets," *Journal of Financial Economics*, 19, 69–90.

Edelen, R., O. Ince, and G. Kadlec (2016): "Institutional Investors and Stock Return Anomalies," *Journal of Financial Economics*, 199, 472–488.

Elton, E., M. Gruber, S. Brown, and W. Goetzmann (2003): *Modern Portfolio Theory and Investment Analysis*, Wiley, Hoboken, NJ.

Frazzini, A. and L. H. Pedersen (2014): "Betting Against Beta," *Journal of Financial Economics*, 111, 1–25.

Greenwood, R. and A. Vissing-Jorgensen (2018): "The Impact of Pensions and Insurance on Global Yield Curves," Harvard Business School - Working Paper 18-109.

Grinblatt, M., S. Titman, and R. Wermers (1995): "Momentum Investment Strategies, Portfolio Performance, and Herding: A Study of Mutual Fund Behavior," *The American Economic Review*, 85, 1088–1105.

Gutierrez, R. and E. Kelley (2009): "Institutional Herding and Future Stock Returns," Unpublished working paper. University of Oregon and University of Arizona.

Jegadeesh, N. and S. Titman (1993): "Returns to Buying Winners and Selling Losers: Implications for Stock Market Efficiency," *The Journal of Finance*, 48, 65–91.

Koijen, R. S., T. J. Moskowitz, L. H. Pedersen, and E. B. Vrugt (2018): "Carry," *Journal of Financial Economics*, 127, 197–225.

Lu, L., M. Pritsker, A. Zlate, K. Anadu, and J. Bohn (2019): "Reach for Yield by U.S. Public Pension Funds," FRB Boston Risk and Policy Analysis Unit Paper No. RPA 19-2.

Maggiori, M., B. Neiman, and J. Schreger (2019): "International Currencies and Capital Allocation," *Journal of Political Economy*, forthcoming.

Merton, R. (1980): "On Estimating the Expected Return on the Market: An Exploratory Investigation," *Journal of Financial Economics*, 8, 323–361.

OECD (2017): "Pension Markets in Focus," http://www.oecd.org/pensions/private-pensions/Pension-Markets-in-Focus-2017.pdf.

Rauh, J. (2009): "Risk Shifting versus Risk Management: Investment Policy in Corporate Pension Plans," *The Review of Financial Studies*, 22, 2687–2733.

Ross, S. A. (1976): "The Arbitrage Theory of Capital Asset Pricing," *Journal of Economic Theory*, 13, 341–360.

Sharpe, W. F. and L. G. Tint (1990): "Liabilities— A New Approach," *The Journal of Portfolio Management*, 16, 5–10.

Shumway, T., M. Szefler, and K. Yuan (2011): "The Information Content of Revealed Beliefs in Portfolio Holdings," Working paper.

van Binsbergen, J., W. Diamond, and M. Grotteria (2019): "Risk Free Interest Rates," Available at SSRN: https://ssrn.com/abstract=3242836.

Vasicek, O. (1973): "A Note on Using Cross-Sectional Information in Bayesian Estimation of Security Betas," *The Journal of Finance*, 28, 1233–1239.

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). 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. Mean returns and standard deviation of returns are measured across time and pension funds for 1999Q1-2017Q4. We also report the mean and standard deviation for equity and fixed income allocations (percent), duration (years), funding ratio (percent), required funding ratio (percent, as of 2007), and ratio of retirees to total participants (percent), computed from the quarterly reports. Panel B reports 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 across funds, and the average kurtosis of the quarterly returns across funds. 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 retirees	35.75	22.22		

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	0.56	4.71	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	0.30	−0.25	−0.27	0.25	−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 (13). 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, using 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 (14) 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 $\hat{\sigma}^2_k$ 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; $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$. 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 (16), 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 contribution 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 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 percentages 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 alpha and the factor exposures for equities and fixed income presented in Equation (21). We calculate per asset class the average return 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 tstats 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 (24): We regress the pension funds equity returns on the factor returns and the factor returns interacted with funding ratio (FR), the inverse of the required funding ratio (1/RFR), ratio of retirees relative to total participants (ratio retiree), size, and asset managers (AM1-AM5) during the period from 2009-2016. Standard errors are in parentheses and clustered at the pension fund level; $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

	Equity returns				
	BM	FR	1/RFR	ratio retiree	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)	(0.1172)	(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%				

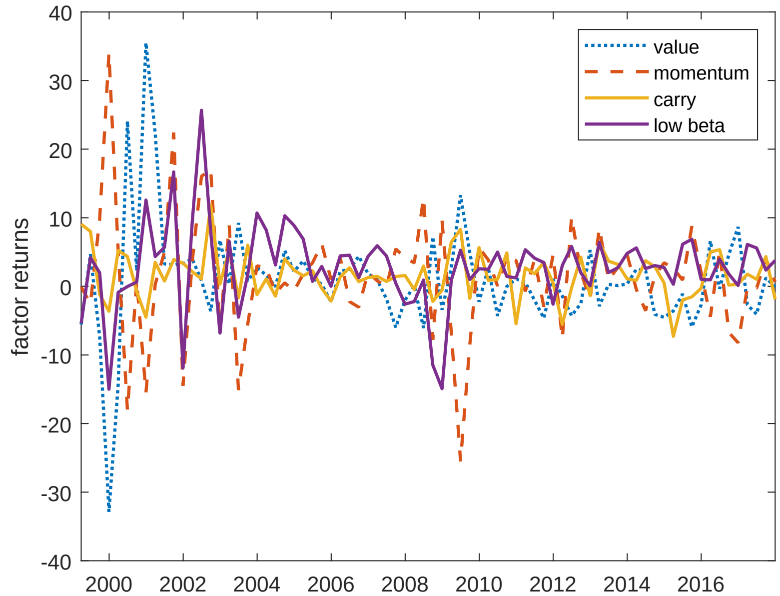
Table 11. **Impact of pension fund characteristics on factor exposures for fixed income**: This table shows the coefficient estimates of Equation (24): We regress the pension funds fixed income returns on the factor returns and the factor returns interacted with funding ratio (FR), the inverse of the required funding ratio (1/RFR), ratio of retirees relative to total participants (ratio retiree), size, and asset managers (AM1-AM5) during the period from 2009-2016. Standard errors are in parentheses and clustered at the pension fund level; $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

	Fixed-income returns				
	BM	FR	1/RFR	ratio retiree	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)	(0.325)	(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
	(0.0558)	(0.2158)	(1.0486)	(0.1545)	(0.0498)
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%				

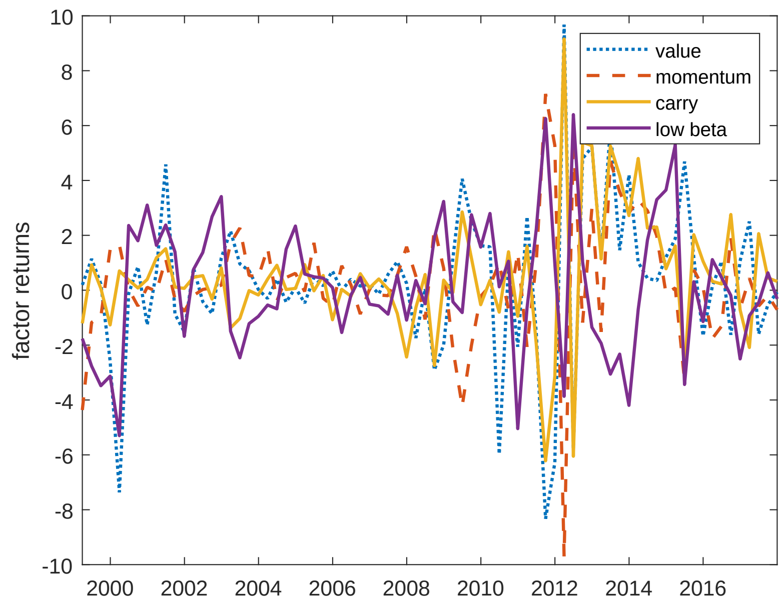
Table 12. **Unconditional - implied beliefs on expected factor returns**: Panel A reports the statistics of the implied beliefs on expected factor returns for equities and Panel B shows the results for fixed income. The results are derived from Equation (25). We report the 10th, 25th, 50th, 75th, and 90th percentiles. All values are in percentages and annualized.

Panel A: Equity returns					
	10th	**25th**	**50th**	**75th**	**90th**
Implied beliefs value	−0.94	0.78	2.25	3.89	5.61
Implied beliefs momentum	−4.36	−3.24	−2.22	−1.19	−0.05
Implied beliefs carry	−2.49	−1.82	−1.09	−0.54	0.04
Implied beliefs low beta	−0.31	1.00	2.16	3.13	4.11
Panel B: Fixed-income returns					
	10th	**25th**	**50th**	**75th**	**90th**
Implied beliefs value	−2.63	−2.23	−1.61	−0.71	−0.20
Implied beliefs momentum	0.10	0.46	1.03	1.43	1.69
Implied beliefs carry	−1.58	−1.33	−0.93	−0.37	−0.05
Implied beliefs low beta	−0.11	0.37	1.55	2.68	3.56

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

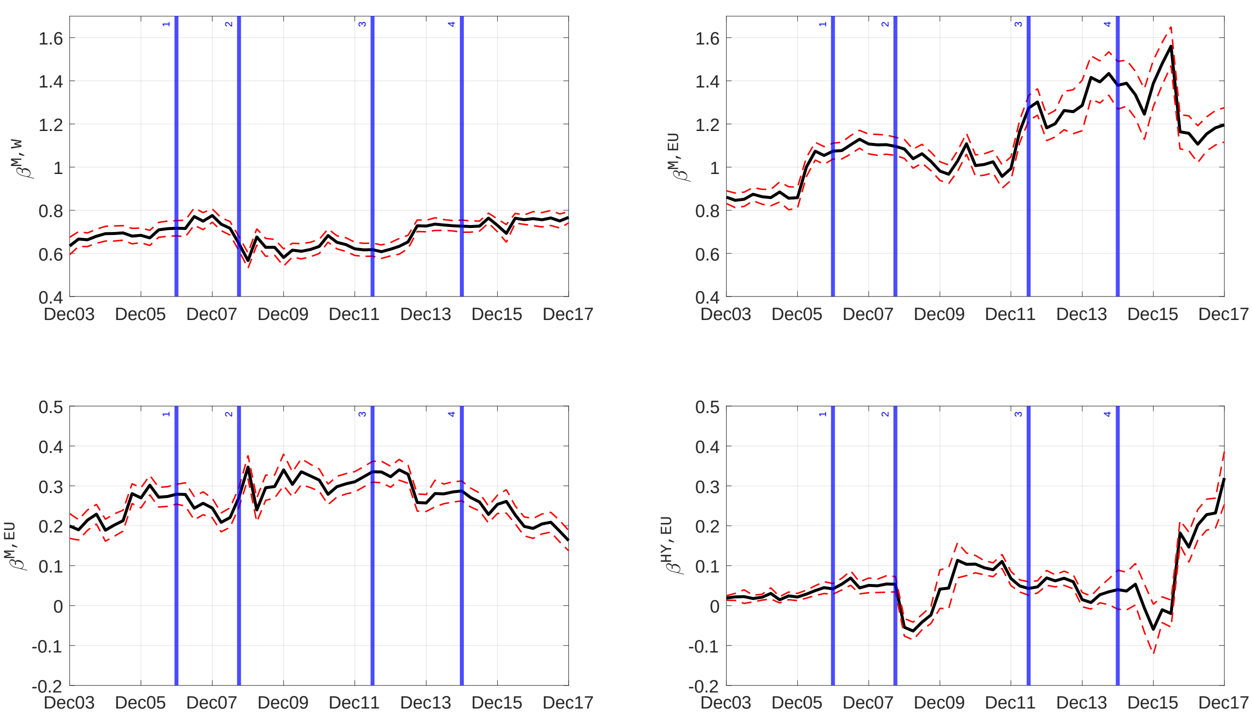


Panel A: Equity long-short factors



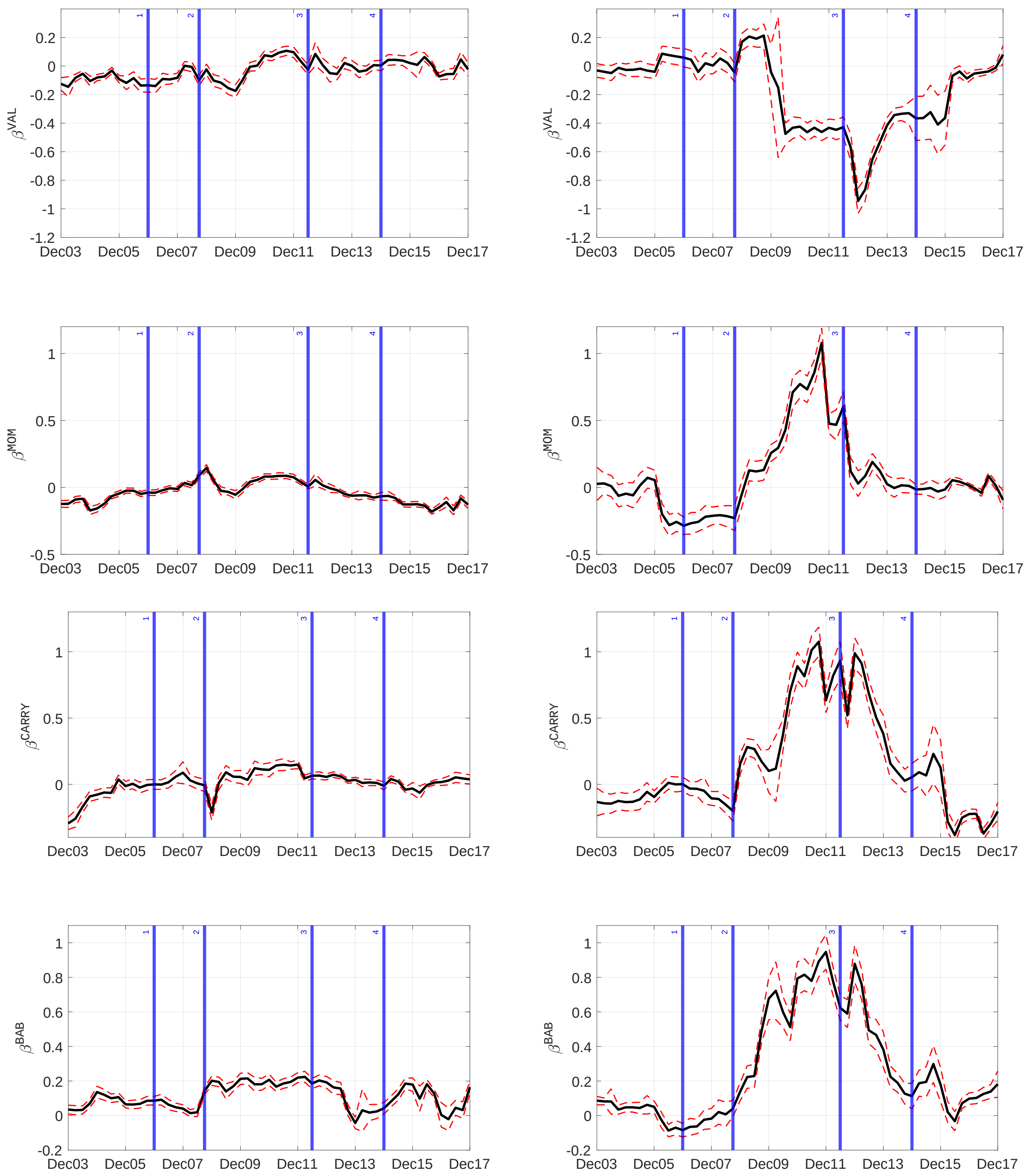
Panel B: Fixed-income long-short factors

Figure 2. **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 28-quarter rolling window. The graphs show the cross-sectional average factor exposures (blue solid line) and the corresponding 95 percent confidence interval (dotted 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 red 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. 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**

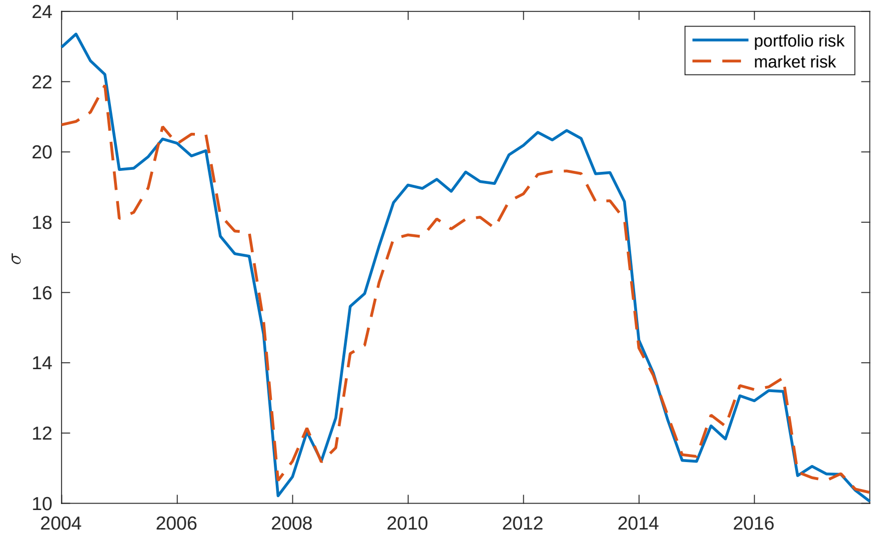
Panel A: Market factors and fixed income credit factor



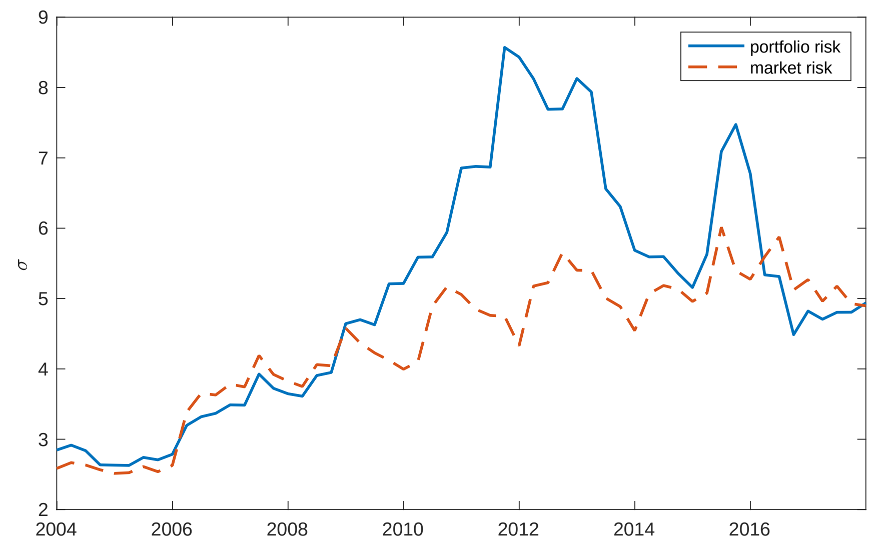
Equities factors **Fixed-income factors**

Panel B: Long-short factors

Figure 3. **Conditional - portfolio risk**: This graph shows the annualized portfolio risk estimated as in Equation (31) for overlapping windows, where the window length equals 28 quarters and $t = w, ..., T$. Next to the portfolio risk, the market risk is depicted, whereby the market risk is measured over the same overlapping window period. Panel A shows the results for equities and Panel B for fixed income.

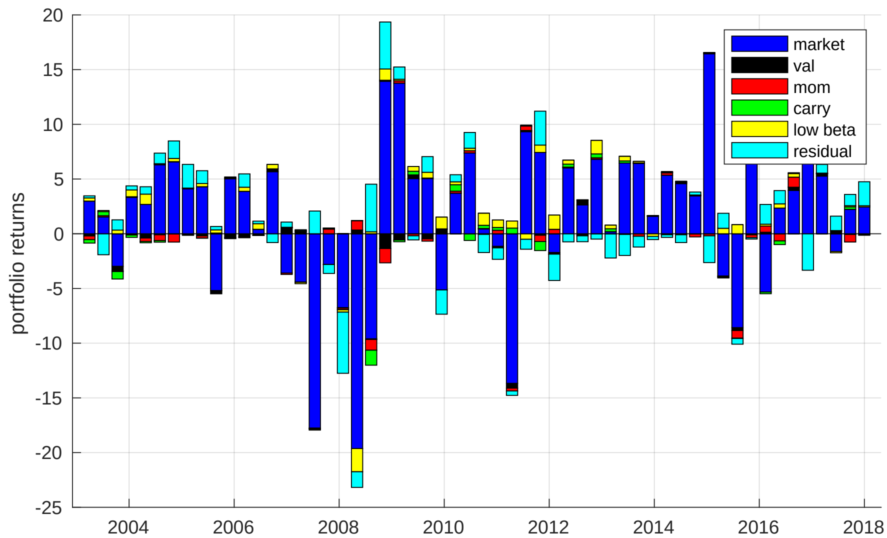


Panel A: Equity portfolio

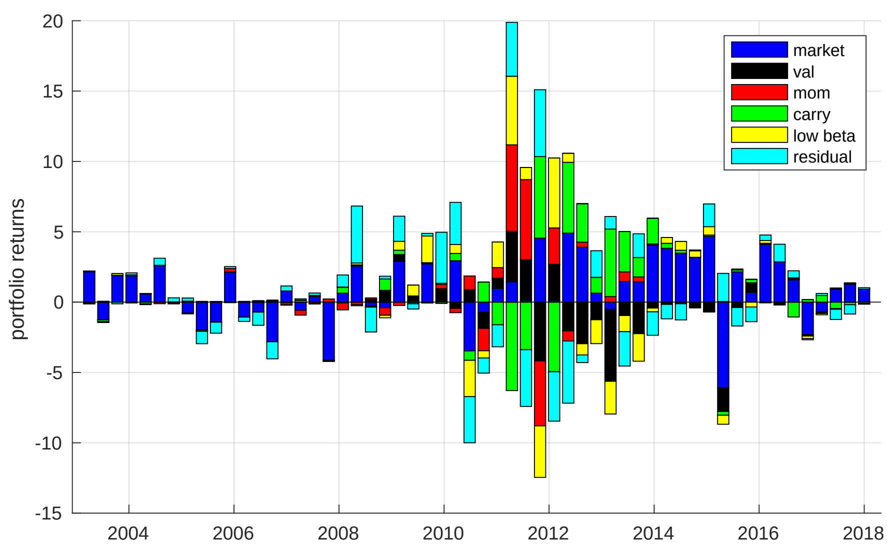


Panel B: Fixed-income portfolio

Figure 4. **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: $\hat{\beta}_{t-1} f_t^k$, where f_t^k is the return on factor k at time t.

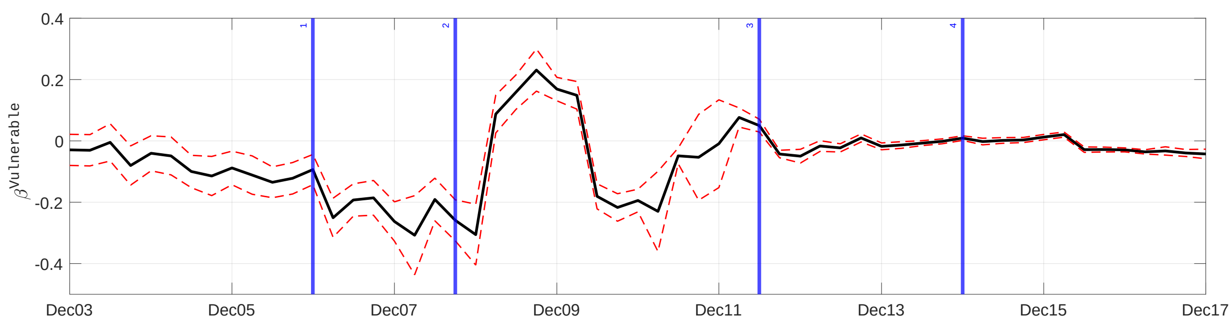


Panel A: Equities factors



Panel B: Fixed-income factors

Figure 5. **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 2005Q1-2017Q4. The estimates are based on a 28-quarter rolling window. The graphs show the cross-sectional average factor exposures (blue solid line) and the corresponding 95 percent confidence interval (dotted lines). The red 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.



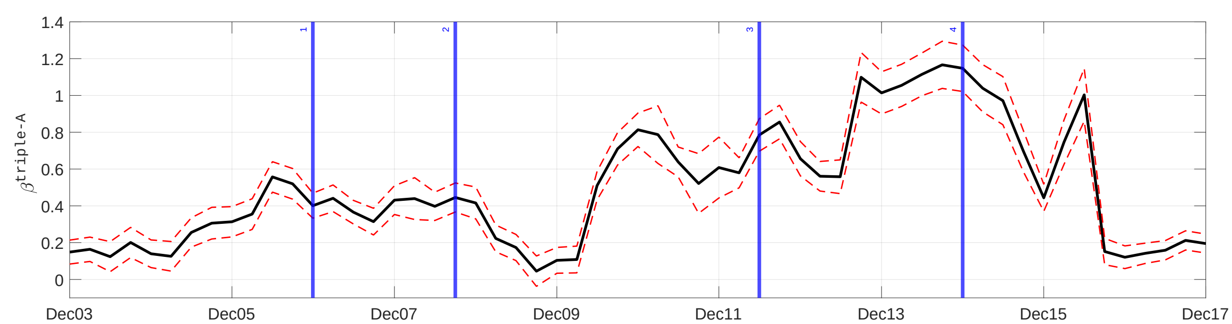
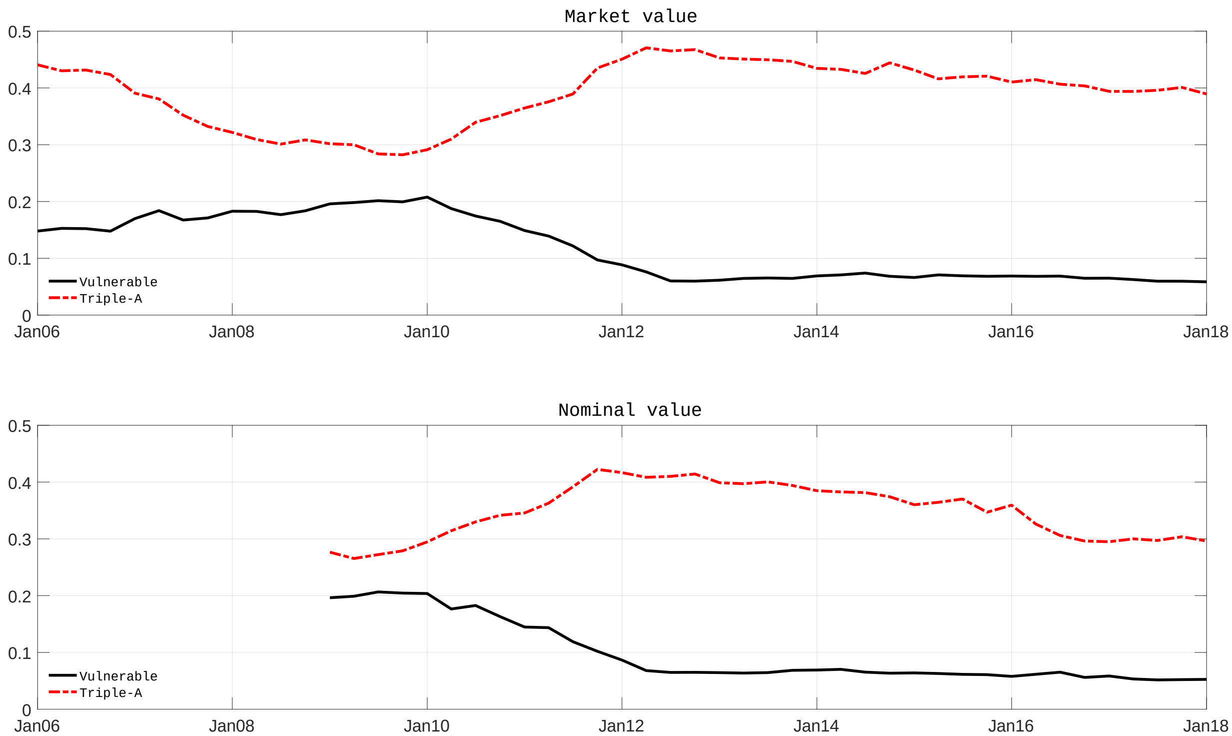


Figure 6. **Holdings in vulnerable and triple-A countries**: This figure shows the cross-sectional average holdings of vulnerable and triple-A countries for fixed income over the period from 2005Q1-2017Q4.



IX. Internet Appendix

A Bloomberg ticker list

Table 13. **Bloomberg ticker list**: This table contains the Bloomberg ticker numbers used to construct the European fixed income factors described in Appendix A. 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 (14):

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

$$G = \mathbb{E}(v_k v_j') = \begin{cases} \sigma^2_{\beta^k} & \text{for} \quad j = k \\ \sigma_{\beta^k \beta^j} & \text{for} \quad j \neq k \end{cases} \tag{40}$$

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.[19]

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 (14) in vector notation:[20]

$$r_i^e = \alpha \iota_T + \beta' f + v_i' f + u_i + \epsilon_i, \tag{41}$$

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 mean zero and variance matrix $\sigma_\epsilon^2 \mathbf{I}_T$. We have

$$\text{Var} \begin{bmatrix} \alpha_i \\ v_i^1 \\ .. \\ v_i^K \\ \epsilon_i \end{bmatrix} = \begin{bmatrix} \sigma_\alpha^2 \iota_T \ \iota_T' & 0 & 0 & 0 & 0 \\ 0 & \sigma_{\beta^1}^2 \iota_T \iota_T' & \sigma_{\beta^1 \beta^2} \iota_T \iota_T' & 0 & 0 \\ 0 & \sigma_{\beta^2 \beta^1} \iota_T \iota_T' & \ddots & 0 & 0 \\ 0 & 0 & 0 & \sigma_{\beta^K}^2 \iota_T \iota_T' & 0 \\ 0 & 0 & 0 & 0 & \sigma_\epsilon^2 \mathbf{I}_T \end{bmatrix}. \tag{42}$$

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

$$V = \text{Var}[r_i^e | f] = \sigma_\alpha^2 \iota_T \ \iota_T' + \sigma_{\beta^1}^2 f^1 f^{1'} + 2\sigma_{\beta^1 \beta^2} f^1 f^{2'} + \sigma_{\beta^2}^2 f^2 f^{2'} + ... + \sigma_{\beta^K}^2 f^K f^{K'} + \sigma_\epsilon^2 \mathbf{I}_T. \tag{43}$$

[19]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, and find the exact coefficients with high precision (i.e., low standard errors) that we imposed for the simulated returns.

[20]Notice that 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:

$$L_i(\alpha, \beta, \sigma_\alpha^2, \sigma_{\beta^1}^2, ..., \sigma_{\beta^K}^2, \sigma_\epsilon^2 | r_i^e) = -\frac{1}{2}\{T \log(2\pi) + \log|V| + (r_i^e - \alpha\iota_T - \beta' f)' V^{-1} (r_i^e - \alpha\iota_T - \beta' f)\}. \tag{44}$$

Then, the total log-likelihood equals:

$$L(\alpha, \beta, \sigma_\alpha^2, \sigma_{\beta^1}^2, ..., \sigma_{\beta^K}^2, \sigma_\epsilon^2 | r^e) = -\frac{1}{2}\{NT \log(2\pi) + N \log|V| + \sum_{i=1}^{N} (r_i^e - \alpha\iota_T - \beta' f)' V^{-1} (r_i^e - \alpha\iota_T - \beta' f)\}. \tag{45}$$

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.[21] 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. We now turn to the long-short factor exposures for equities. 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 between −0.09 and 0.29.

In case of fixed income, pension funds have an average (significant) exposure to the market index 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), and a slightly positive exposure to momentum (0.07) and strong positive exposure to low

[21] In the next section, we show that an important determinant for the degree of home-currency bias is the size of a pension fund. Small pension funds allocate more to Europe.

beta (0.28). The exposure to value varies between −0.51 and 0.09, between −0.24 and 0.08 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 detect statistically 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 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 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).

Table 14. **Country allocation equities**: This table shows the 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), and United Kingdom (GB), United States (US).

						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%
Oct-12	3%	3%	6%	5%	2%	1%	13%	6%	2%	2%	5%	13%	39%

Date	AU	CA	FR	DE	HK	IT	JP	NL	ES	SE	CH	GB	US
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 15. **Country allocation fixed-income**: This table shows the 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 United Kingdom (GB).

	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 16. **Country AUM fixed-income *nominal value***: This table shows the *nominal* AUM (in millions) invested in the following countries for equities: 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 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