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

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Pension fund equity performance: Patience, activity or both?*

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Abstract

We study how pension fund (out)performance is influenced by a) a pension fund's activity, i.e., how much the pension fund deviates in its stock allocation from the typical pension fund behavior, and b) whether the pension fund exploits short- or long-term mispricing opportunities (measured by stock holding duration). We do not find that high activity or higher holding duration, separately, lead to higher risk adjusted returns on average. However, if high activity is paired with long-term holdings, the pension fund's performance increases. Quantitatively, if an active pension fund with a duration of one year increases its duration by one month, annual returns tend to increase by 3.3%. Our findings indicate that some pension funds are patient enough to exploit long-term mispricing opportunities.

Keywords: Pension funds; Active share; fund duration.
JEL classifications: G11, G23, H55.

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1. Introduction

Pension funds provide the main source of income for the elderly and the retired. As such, plan participants are looking for—and expect—a predictable and safe retirement income, and rely on pension funds to manage their retirement savings safely and effectively. Recent developments, however, such as the 2008 financial crisis, the subsequent low interest rate environment, and changing demographics of pension fund participants have put a lot of pressure on the system. The result has been, among other things, widespread benefit cuts. It is therefore of great importance to understand factors driving the performance of pension fund investments.

Our paper investigates the role of activity and patience in pension fund equity investments. Active investing, which we measure as the deviation from the *typical* strategy of other pension funds, can attract supervisory scrutiny, harm reputation, and increase costs. If a pension fund decides to invest actively, then identifying whether the fund's deviation from the *typical* strategy of other pension funds is beneficial and improves performance is relevant to the pension funds' stakeholders. Since plan participants save for years (decades) for their retirement, pension funds are the textbook example of investors with a long-term investment horizon. This long-term horizon could potentially allow pension funds to exploit long-term mispricing opportunities. Cremers and Pareek (2016) provide evidence that pension funds are indeed active in searching for opportunities to do just that. Our paper provides evidence that pension funds that invest actively by deviating from their peers, while at the same time exploit long-term mispricing opportunities (measured in stock holding duration), outperform their peers.

Cremers and Petajisto (2009) introduced a novel measure of active management termed *Active share*, which is based on a comparison of the fund holdings with those of its benchmark. The *Active share* measure is widely used in the financial industry; for example, it is incorporated in Morningstar Direct and FactSet. We construct a similar measure for pension funds, *Active share*^{PF}, for which, rather than considering how equity holdings deviate from the holdings of a self-proclaimed benchmark, we identify how the holdings deviate from the equity holdings of other pension funds. Our modification of the reference point (using median holdings rather than benchmark holdings) is motivated by strong evidence in favor of herding among pension funds (e.g., Broeders, Chen, Minderhoud, and Schudel (2016), Koetsier and Bikker (2017, 2018)). Using this new measure of pension fund activity, we evaluate the extent to which a particular pension fund pursues its own strategies.

Active pension funds can follow short- and long-term investment strategies. Shleifer and Vishny (1997) argue that it might be too risky for fund managers to bet on long-term mispricing since it takes time to reveal successful strategies. Temporary setbacks while waiting for return could cost the manager her or his position. Exploiting long-term mispricing is, therefore, difficult and expensive. At the same time, these difficulties could make long-term strategies more profitable. We determine the degree of patience of a fund by stock holding duration. To do so, we measure the average length of time a fund held a particular individual equity position in its portfolio over the past two years. As such, holding duration can capture the extent to which pension funds focus on short-term or long-term mispricing opportunities. Focusing on the investment horizon is also motivated by evidence on the significance of the short-term and long-term strategies in the mutual fund industry (Lan, Moneta, and Wermers, 2015).

Cremers and Pareek (2016) show that mutual funds that both deviate substantially from their benchmarks and are patient in their strategies can achieve significant outperformance. Their empirical analysis provides evidence that a particular subset of high-duration mutual funds—that also exhibit high *Active share* holdings—can achieve an outperformance of around 2% per year, which is significant. We analyze whether a similar effect can be found for the arguably more patient pension funds, in particular in the established Dutch pension funds market.

We find that our novel measure of pension fund activity is not related to better performance in general, i.e., higher activity does not imply higher performance. However, when we add an additional dimension and distinguish pension funds focused on patient strategies, we are able to identify that pairing activity and pursuing long-term mispricing opportunities improves fund performance. At the same time, we observe that funds that invest actively in strategies with low holding duration do not exhibit higher performance. Moreover, this effect is found not only across funds but also within the fund. In times when the fund is active and patient, its performance is superior.

To support our main findings, we replace fund holding duration by *turnover* (following the definition of the U.S. Securities and Exchange Commission (SEC)) in the robustness section. In the mutual fund industry, Pástor, Stambaugh, and Taylor (2017) find predictive power of turnover across the time-series dimension. They argue that, although turnover is not able to explain performance differences in the cross-section of mutual funds, the measure is informative about individual fund performance over time. Our analysis of pension funds provides evidence that turnover is indeed a factor that can be used to explain the variation in returns both across, and within funds.

The Dutch pension system, one of the world's most comprehensive, provides an ideal environment to examine funds' investment performance. The system is largely pre-funded and the 268 pension funds have around €1.3 trillion assets under management. Although some funds have been under pressure, no individual fund has been in outright distress. The funds' investment behavior is thus not disturbed by fire-sales. Moreover, for the largest 39 pension funds, we can track the monthly asset allocation at the individual security (ISIN) level. This detailed dataset covers pension fund individual holdings in more than 20,000 unique securities. Collected for supervisory purposes by the Dutch Central Bank (DNB), it provides us with a unique opportunity to analyze pension fund investment activity and performance.

Our paper, and, in particular our measure of active investment—defined as deviations from the typical pension fund holdings—is motivated by recent evidence of herding in the pension fund industry. Specifically, Broeders et al. (2016) document strong evidence supporting different types of herding in the Dutch pension funds market. They demonstrate that pension funds use similar rebalancing strategies, exhibit similar reaction to external shocks, and replicate changes in their strategic asset allocation. Koetsier and Bikker (2017, 2018) investigate the strength of herding across different asset classes and identify its determinants. Furthermore, Blake, Sarno, and Zinna (2017) find strong support of herding for the universe of UK pension funds. They conclude that herds consist of same-sized funds with similar sponsor types. In addition, Raddatz and Schmukler (2013) report a similar pattern in the Chilean pension fund industry, while Voronkova and Bohl (2005) find evidence of herding in the Polish pension fund market. These findings are related to those in the mutual fund industry; see, for example, Hunter, Kandel, Kandel, and Wermers (2014) for a discussion of the importance of active peer benchmarks in investment allocation.

The papers further complement the literature on pension fund performance (Coggin, Fabozzi, and Rahman, 1993; Blake, Lehmann, and Timmermann, 1999) and on the ability of pension funds to outperform the market. However, while performance drivers for mutual funds have been extensively analyzed and are well-understood (see, for example, Carhart (1997), Fama and French (2010), Berk and van Binsbergen (2015) or Gallefoss, Hansen, Haukaas, and Molnár (2015)), the literature on pension fund performance is relatively scarce. Key studies related to our research include the following. Antolin (2008) provides a comprehensive international summary of pension fund performance and discusses individual specific features. Bikker, Broeders, Hollanders, and Ponds (2012) stress that the age of pension fund participants is a crucial indicator for the fund's asset allocation. Andonov, Bauer, and Cremers (2012) analyze the performance of U.S. pension funds and find that an annual net alpha of 89 basis points stems in equal part from asset allocation, market timing, and security selection. Finally, Duijm and Steins Bisschop (2018) examine the difference between the performance of short-term and long-term investment strategies employed by pension funds and insurance companies. However, they do not find any evidence of long-termism in pension funds.

2. Methodology

We introduce two measures—*Active share*^{PF} and *Duration*—to investigate the effects of activity and patience, respectively, on pension fund equity performance. In this section, we discuss the exact definitions of these key variables and describe the models we estimate to address our research question.

Active share^{PF}

Our new measure of pension fund activity, *Active share*^{PF}, was inspired by the popular measure of mutual fund activity - *Active share*. The latter was introduced in Cremers and Petajisto (2009) and measures the proportion of a fund's holding in equity that is different from the benchmark. Motivated by substantial evidence on herding in pension funds (e.g., Broeders, Chen, Minderhoud, and Schudel (2016) for the Dutch pension funds market), we aim to capture activity as the deviation from *what everybody else does* rather than as the deviation from a self-proclaimed benchmark. Previous evidence (see e.g., Acharya and Pedraza (2016)) documents that it is not performance above the benchmark, but rather performance relative to its peers (i.e., other pension funds) that is relevant for the reputation of a fund.

Therefore, we modify the original *Active share* definition and construct our measure *Active share*^{PF} as the proportion of the fund's holdings in equities that is different from the median holding in each stock of all pension funds in our sample. *Active share*^{PF} is calculated as

$$Active\ share^{PF}_{i,t} = \frac{1}{2} \sum_{j \in Q_{i,t}} \mid w_{i,j,t} - w_{median,j,t} \mid \qquad (1)$$

where $w_{i,j,t}$ denotes the weight of stock j in pension fund i at time t, and $w_{median,j,t}$ denotes the median holding of stock j at time t calculated over the holdings of that particular stock of all pension funds in our sample. By definition, if less than half the pension funds invest in stock j then the corresponding weight $w_{median,j,t}$ is equal to zero. $Q_{i,t}$ is the set of all stocks in which the fund i is invested at time t. If *Active share*^{PF} is close to 100%, it indicates that a pension fund's portfolio is completely different from the benchmark comprising the median holdings. If *Active share*^{PF} is equal to 0%, then a pension fund would hold exactly the median holding in each stock.

We use the median weights instead of the mean weights as the benchmark for the following reason. If there is a stock that only a few funds hold in their portfolio, considering the mean as a benchmark would introduce a non-zero activity for all funds—that is, for those that both hold the asset, and those that do not. However, implementing the median as a benchmark imposes a non-zero activity for those funds that hold this specific asset. It is this fund behavior that we aim to capture.

Duration

We measure the patience of a fund by stock holding duration, as introduced in Cremers and Pareek (2015). *Duration* measures the weighted average period that a fund has held equities in its portfolio over the last two years. First, the stock holding duration is calculated for each stock j in every pension fund i as a weighted sum of buys and sells over the last R months. The formula is given by

$$Duration_{i,j,T-1} = \underbrace{\frac{(R-1)H_{i,j}}{H_{i,j}+B_{i,j}}}_{Initial\ holdings} + \underbrace{\sum_{t=T-R}^{T-1}\left(\frac{(T-t-1)\alpha_{i,j,t}}{H_{i,j}+B_{i,j}}\right)}_{Buying\ and\ selling} \tag{2}$$

where $H_{i,j}$ denotes the percentage of total shares outstanding of stock j held by fund i at time $t = T - R$. $B_{i,j}$ denotes the total percentage of shares of stock j bought by fund i between $t = T - R$ and $t = T - 1$. We drop the time subscript for notational simplicity. The percentage of total shares outstanding of stock j bought or sold by fund i between $t-1$ and t is given by $\alpha_{i,j}$, which is positive for buys and negative for sells. Intuitively, we want to weigh a fund's buys and sells by the length of time the stock is held over a certain period. We capture these changes in holdings with our measure by taking the initial holdings of a stock with the weight for the entire period considered (the second term) and adjust the maximum duration for buys and sells (the first term). Selling reduces the portfolio duration while buying increases it. Furthermore, the aggregate duration of a fund at $t = T - 1$ is calculated as the value weighted average of all single stock durations:

$$Duration_{i,T-1} = \sum_{j \in Q_i} w_{i,j,T-1} Duration_{i,j,T-1} \tag{3}$$

We choose to use an observational time range of $R = 24$ months, which is long enough to reveal the informational strategy of funds while guaranteeing sufficient observations over time to explore its predictive power. A low value of *Duration* indicates that a fund does not hold assets for a long period and that assets are traded frequently. In such cases a fund manager assumes that information is incorporated into stock prices in the short-term. In contrast, a fund with a higher value of *Duration* focuses on exploiting mispricing opportunities over a longer term, requiring fund managers to be patient.

2.1. Regression models

To capture the effects of the activity and patience of pension funds on their performance we employ several models. First, we run predictive panel regression models for each measure separately as in

$$R_{i,t} = \alpha_i + \beta High\ active\ share^{PF}_{i,t-1} + \gamma Controls_{i,t-1} + \epsilon_{i,t} \quad (4)$$

$$R_{i,t} = \alpha_i + \beta Duration_{i,t-1} + \gamma Controls_{i,t-1} + \epsilon_{i,t} \quad (5)$$

where $R_{i,t}$ is the risk-adjusted return of fund i in month t. By *Controls* we denote a set of other relevant variables, which includes fund size and the percentage of assets allocated to equity, as well as two variables describing the pension fund participant structure; the ratio of active to retired participants, and a Herfindahl index of the age structure of the active participants. A higher value on the first measure implies a longer investment horizon. A higher concentration in the age profile (higher Herfindahl), however, implies a more irregular fund outflow, which might be undesirable for a pension fund. All control variables are further described in Section 3.

We focus on predictive relation rather than contemporaneous dependence because the latter might be contaminated by managers' trading as a reaction to return rather than reflect managerial skill with respect to patience and activity. Nonetheless, we investigate the contemporaneous relation between the return and the measures of activity and patience in the robustness section.

In the analysis, we are interested in both the cross-sectional and the time-series changes of the pension funds' performance. In the baseline model, we assume the same intercept for any fund i and any period t. Later, we also account for time fixed effects by assuming a period-specific α_t for every year t. This addition of year fixed effects controls for any unobserved variables that change over time but not across pension funds, such as macroeconomic changes, new regulations, or financial market turbulence. Therefore, we analyze whether patience and activity can predict different return patterns in the cross section of funds accounting for macroeconomic unobservables. A significant coefficient documents that the corresponding activity or patience measure disentangles funds with lower and higher returns.

Furthermore, the model specifications with fund fixed effects could shed light on the time-series variation within each fund. In this setup, we assume a fund-specific α_i, which allows us to study whether a pension fund's activity and patience explain the changes in performance within a particular pension fund over time. Thus, we test whether an increase in the patience or activity measure of a pension fund is associated with higher or lower returns.

Deviating from the peers might only be beneficial in specific cases, e.g., when funds focus on investments requiring less patience (short-term investments) or at times in which much more patience in holding their positions is required (long-term investments). Therefore, we extend our initial regression model by including both measures in one specification, as well as their interaction term:

$$\begin{aligned} R_{i,t} &= \alpha_i + \beta_1 High\ active\ share^{PF}_{i,t-1} + \beta_2 Duration_{i,t-1} \\ &+ \beta_3 High\ active\ share^{PF}_{i,t-1} \times Duration_{i,t-1} + \gamma Controls_{i,t-1} + \epsilon_{i,t}. \end{aligned} \quad (6)$$

The interaction term enriches our model by relaxing the assumption that the effects of activity on performance are fixed, especially when a fund exploits either short- or long-term investment opportunities. In a regression specification without fund fixed effect, a significant positive coefficient β_3 indicates that funds with high activity, in particular in long-term investments, deliver higher performance. At the same time, funds that use a short-term investment strategy do not profit from this activity.

In a regression model with fund fixed effects, the beta coefficients reflect only the contribution to the performance of the within-fund variation and this setup, therefore, allows us to explore the time series patterns. A significant positive coefficient would provide evidence that, when a fund increases its activity with a focus on long-term investments, its performance also increases. A negative significant coefficient, however, would indicate that higher activity in long-term investments does not pay off.

Using the methodology outlined above, we explore how pension fund's activity and patience affects fund performance. In particular, our interest lies in developing a better understanding of whether our measures are able to predict differences in performance across funds and within a fund over time.

3. Data and summary statistics

In order to compute our measures of *Active share*^{PF} and *Duration*, we need data on the portfolio composition of the pension funds. In the Netherlands, the Dutch Central Bank requires the largest 39 pension funds to report their investment holdings on the individual security level on a monthly basis. Each holding is uniquely identified by its International Securities Identification Number (ISIN).[1] We restrict our sample to all holdings classified

[1] As to date, there are 268 active pension funds operating in the Netherlands. The largest 39 pension funds – the so-called system relevant pension fund – manage roughly 82% of all assets under management

(by the reporting pension funds) as listed equity. For each ISIN the pension funds report the value and number of shares held at the beginning and end of each month, as well as the value and number of shares bought and sold each month. Our final dataset covers the period from April 2009 until December 2016.

For two funds in our sample, ABP and Zorg en Welzijn[2], the reporting requirements differ. Both funds have their own, legally independent, asset management companies: APG and PGGM, respectively. In addition to ABP and Zorg en Welzijn, who have most of their assets invested through these companies, three other pension funds in our sample also have a portion of their equity (ranging from, on average less than 1/10 to 2/3) invested through either APG or PGGM. The pension funds do not report the granular breakdown of their assets invested through APG and PGGM themselves. However, both APG and PGGM report their holdings on the ISIN level to the DNB for all their investment pools. Separately, the DNB collects data from the pension funds that use APG and PGGM to determine how much each fund is invested in each of the investment pools. Using the latter dataset, we are able to generate a look-through and retrieve positions held by these five pension funds.

Our monthly unbalanced panel dataset is augmented with further pension fund characteristics reported to the Dutch Central Bank on a quarterly basis. These characteristics include the funds' assets under management, the division of the assets into different asset classes, the coverage ratio, fees and asset managers' mandates, and information on the pension funds' participants (e.g., age structure, number of active and retired participants). Using their ISIN number, we match the holding information to stock price data from Datastream. We calculate monthly value-weighted returns based on all ISINs for which stock price data is available.

To control for the exposure to various recognized risk factors we also calculate risk-adjusted returns. In particular, we calculate the factor loadings of each stock return to the three or five global 'Fama-French'-factors, and the factor exposure as a product of the factor loading and the current factor value.[3] The risk-adjusted returns are given by the difference between the stock returns and the sum of all factor exposures. We construct the risk-adjusted fund returns using the value-weighted risk-adjusted stock returns.

Descriptive statistics for the pension funds in our sample are shown in Table 1. Our sample consists of 39 pension funds covering the period from April 2009 to December 2016,

(€1,042 billion of €1,265 billion) (December 2016).

[2]ABP's members are civil servants while Zorg and Welzijn focuses on the medical and care profession.

[2]The results of our analysis are robust to excluding these funds from the sample. As a further robustness check we also include an indicator variable in our regression analysis to flag the pension funds involved.

[3]Factors are provided by Kenneth French. See http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

yielding 3,173 fund-month observations. Panel B of Table 1 summarizes the characteristics of the main variables in our analysis. The mean value of *Active share*^{PF} is 41.1% (with a median value of 39%), indicating that Dutch pension funds have a substantial overlap in their stock investments. Within the sample, we observe values of *Active share*^{PF} ranging from 14% to 96%. The mean (median) holding *Duration* is 0.94 (0.97) years with a substantial standard deviation of 0.34 years. Note that for calculating *Duration* we require a time range. We have chosen an evaluation period of 24 months, reducing the number of available observations.

To better understand the composition of the funds' holdings, we also report the number of unique stocks held per month. The mean number of stocks held per month is 1,815. The number of stocks held in the portfolio varies significantly from 65 to 6,665 stocks. On average, market data is available in Datastream for more than 94% of the stocks reported. The average monthly fund return net of the market return is 1.1%, which equates to an annualized average return of 13%. If we adjust the individual stock returns by the global three or five Fama-French factors[4], the pension fund risk-adjusted returns decrease to 0.6% per month.

Finally, in Panel C of Table 1 we report the pension fund characteristics that we use as control variables in our multivariate regressions. While the variables are reported and available at quarterly frequency, Panel C only reports end of the year values (quarter 4) to provide a clearer picture of the characteristics of the pension funds in our sample. Our sample consists of a range of different pension funds. The smallest pension fund in our sample manages assets with a value of just below €1 billion while the largest pension fund has €367 billion in assets under management. On average, 31% of these assets are held in equity (ranging from 13% to 53%). The distribution of active participants, measured by the Herfindahl Index of reported age categories,[5] varies widely between the funds in our sample, ranging from 0.1 to 0.6.[6] This heterogeneous group of funds provides an optimal sample with which to test whether fund (out-)performance is related to *Active share*^{PF} and *Duration*, i.e., whether their activity and patience are interconnected when it comes to evaluating their strategies.

For constructing the *Active share*^{PF} measure, we benchmark pension funds' equity holdings against a typical fund. This benchmark is constructed by calculating, for each month, the median holding from all pension funds for each ISIN. This means that an ISIN receives

[4]See Fama and French (1993) and Fama and French (2016) for 3 and 5 factors, respectively

[5]Pension funds report the age of participants in five year brackets, ranging from 20 to 95 years. The remaining participants are either classified as *younger than 20* or *older than 95*.

[6]During our sample period the pension funds varied in their financial health as measured by the coverage ratio. While the mean value of 110.2% is slightly above the DNB target, the minimum value reported was 88%.

a positive weight whenever 50% or more of the pension funds are invested in that particular ISIN during a month. Otherwise, the weight of the ISIN is zero. Over our sample period, the *median fund* consists of 2163 different ISINs. On average, each month, the *median fund* is invested in 1,119.6 (median 1,197) different stocks ranging from 389 at the beginning of our sample period to 1,597 in later months.

Figure 3 plots the fraction of stocks in the benchmark allocated to different geographic regions over time. Over our sample period, we observe a slight reduction in the number of European stocks with non-zero median weights and an increase in stocks from the Pacific region (Japan, Australian, New Zealand, Singapore etc.). Of note, 97% of the stocks in the benchmark are developed market stocks.[7]

Furthermore, Table 2 provides an overview of the pairwise correlations of the variables used in this study. *Active share*^{PF} is negatively correlated with a fund's holding duration (correlation of 18% and significant at the 5% significance level) indicating that pension funds that deviate from their peers tend to be less patient. Conversely, there seems to be a weak positive relationship between pension fund size and activity of the fund. Moreover, larger funds also tend to hold assets for a longer period (correlation of 12.5% and significant at the 10% significance level). Finally, pension funds that hold a higher fraction of equity seem to be more active (i.e., deviate more from the typical fund). However, they have no clear preference between short or long-term holdings (the correlation is only 0.05 and not significant).

Finally, in Figure 1, we plot the time dynamics of the average and median *Active share*^{PF} (left) and *Duration* (right). The median *Active share*^{PF} in our sample is equal to 47% in January 2009 and gradually decreases to 36% by the end of our sample period. This pattern is consistent with a shift towards passive investing in equities. Pension funds have recognized that it is difficult to consistently realize outperformance. Therefore, they now tend to prefer the cheaper passive investment style. While the median value in the first half of the sample is more volatile, the median fund activity measure has been more stable since the end of 2013. Median fund duration in our sample equals 9 months in 2011 (0.75 years), gradually climbs to almost 13 months in 2014 (1.05 years), after which it drops slightly and stays around 12 months until the end of the sample period. Moreover, duration among funds is less diverse at the beginning of the sample than at the end, i.e., the difference between the 75^{th} percentile and 25^{th} percentile is 2.75 months in January 2011 (0.23 years) and doubles to 5.5 months in January 2016 (0.45 years). This increase in diversity indicates that the variability of funds in patience increases at the end of our sample period.

[7] We follow the MSCI classifications with regard to geographic region and market type.

4. Activity and Patience

To document the potential effects of patience and activity on the performance of pension funds we run several predictive panel regressions with the monthly fund returns explained by the above defined variables of patience and activity and, as control variables, other relevant fund characteristics. Our focus is on the two main variables: *High Active share*^{PF}, defined as a dummy variable that is equal to one if the value of *Active share*^{PF} lies in the third tercile that month, and zero otherwise;[8] and a continuous version of *Duration*. In addition to our main variables of interest we consider fund characteristics such as the percentage of equity in the fund's portfolio, the natural logarithm of the total investment of the fund, the percentage of active to retired participants, and the Herfindahl index for the age of active participants. The dependent variable is the risk-adjusted fund return.

Figure 2 plots the *Active share*^{PF}–tercile allocation of each fund over time. Clearly, our overall sample consist of funds that have a consistent high (or low) *Active share*^{PF}, as well as those that change their strategy throughout the sample period. The present variation in the activity variable provides us with a proper environment in which to study its effects.

The results from the individual regressions for the fund return adjusted by different risk factors are presented in Table 3. Panel A reports results for the market-adjusted results, and Panels B and C consider returns adjusted by the three and five Fama-French factors, respectively. The results are quantitatively and statistically similar for all three risk adjustments of returns. First, we study the effects of activity and patience separately. Column (1) shows that pension funds with *High Active share*^{PF} do not deliver significantly different performance relative to funds with lower activity (the cross-sectional effect). Moreover, the coefficient on the *High Active share*^{PF} remains insignificant if we focus our attention on a particular fund, i.e., if we include firm fixed effects (and also year fixed effects) into the regression specifications. Column (2) indicates that a high value of *Active share*^{PF} of a fund is not accompanied with a significant change in the performance of the fund (the time-series effect).

The results for our second variable of interest, *Duration*, are reported in Columns (3)-(4). Pension funds with lower *Duration* tend to have higher performance in the cross-sectional comparison. However, this effect is only significant for the market-adjusted returns and it disappears if we adjust the returns for the Fama-French factors. For *Duration*, we similarly find no consistent significant pattern in the time-series (see Column (4)). In summary, we do not observe any significant dependence at the univariate level.

[8] We opt for modeling activity as a dummy variable based on the *Active share*^{PF} to allow for a non-linear relationship to performance.

In Columns (5)-(6) we continue with a multivariate analysis and include both, the activity and the patience measures. The results convey the same message we found in the univariate regressions: the coefficients of both variables are not consistently significant and there seems to be no predictive power to explain the performance of pension funds, by either the active behavior or the duration of fund holdings.

We find the most interesting results when we include an interaction term of the activity and patience measures in the regression analysis. Column (7) reports on the cross-sectional analysis results. We find that, with more activity and longer duration, performance decreases (β_1 and β_2 are negative), while the interaction of activity and holdings duration has no significant effect on fund performance. However, if we include time fixed effects and, thus, control for unobservable macroeconomic variables that change over time (Column (8)), the significant and positive coefficient of the interaction term indicates a profitable combination of long-term holdings and deviation from the standard holdings of the pension fund industry. In particular, if a fund exhibits low activity (*High Active share*^{PF} is zero), then the performance of the pension fund decreases with longer holdings (i.e., β_2 is negative). However, if a fund exhibits high activity (*High Active share*^{PF} is one), the performance is positively related to duration (i.e., $\beta_2 + \beta_3$ is positive).

The interaction term remains significant in the time-series analysis both without year fixed effects (Column (9)) and with it (Column (10)). We find a strong positive effect between *Active share*^{PF} and *Duration* at the fund level. If the fund deviates from its peers (high *Active share*^{PF}) and focuses on longer-term investment opportunities (high *Duration*), its performance tend to improve. On the other hand, if a fund's active stance deviates from the other funds while it simultaneously focuses on short-term mispricing, its performances does not improve. In the case of both time and fund fixed effects, the importance of the interaction term is clear from a comparison of the results in Column (10) to their equivalents in Column (6) without the interaction term. Column (6) shows that the performance of the pension fund is sensitive to neither activity nor duration, and funds deliver the same performance regardless of these values. However, results in Column (10) reveal that the pension funds that exhibit both high activity *and* high duration do outperform. Quantitatively, if a fund with a duration of one year increases its duration by one month, and if this fund is also active, then the fund is rewarded with a 3.3% higher return (annualized). If the pension fund is not active, however, the increase in duration is accompanied by a 2.2% drop in the return.

Figure 4 illustrates the additional value of including the interaction term in the model. The model without the interaction term (left panel) shows that there is basically no effect of fund patience or activity on performance. A flat surface documents that neither variable has predictive power to explain future returns. However, when we consider a joint effect and include the interaction term (right panel), we identify times when funds have better performance and find high sensitivity to values of *Duration* and *Active share*^{PF} (the surface is steeper along both dimensions). In particular, in times when funds are more active and hold assets longer, they are able to deliver higher returns.

In summary, we find that being active in the pension fund industry by itself does not produce a significant effect. However, our expanded analysis shows that an active stance pays off, but only in combination with a specific type of strategy (i.e, long stock holding duration).

5. Robustness

In Section 4, we established our main result—that the returns of pension funds that deviate most from the median holdings are sensitive to asset holding duration. Specifically, the equity portfolios of funds with high *Active share*^{PF} perform better if the fund pairs its active strategy with patient investments. This result is robust to various alternative specification, as we discuss below.

5.1. Low activity with long-term holdings—placebo test

In the first robustness test, we replace the *High Active share*^{PF} dummy with a *Low Active share*^{PF} dummy. The dummy variable in the table now indicates those funds that are in the *lowest* tercile of *Active share*^{PF} values, i.e., the funds which deviate least from the benchmark. Table 4 displays the results from this placebo test where the tabulated specification corresponds to Columns (7) and (10) of Table 3 for the three different return measures. Using the *Low Active share*^{PF} dummy variable, we find no significant coefficient for any of our three main variables: *Active share*^{PF}, *Duration*, nor the interaction of both. This result is line with our main hypothesis that a fund needs to commit to an active strategy to exploit long-term mispricing.

5.2. Alternative duration measure

To mitigate concerns that our results are driven by the choice of our duration measure, we re-estimate our main model with an alternative measure for holding duration: *Turnover*. We follow the definition of turnover from the U.S. Security Exchange Commission mutual fund reporting requirements. For each month in our sample, we calculate a pension fund turnover based on the prior 12 month holdings information. Turnover for fund i at time $t-1$

is defined as

$$Turnover_{i,t-1} = \frac{\min\left(buys_{i,t-1}, sells_{i,t-1}\right)}{\text{avg}\left(total\ assets_{i,t-1}\right)} \tag{7}$$

where the numerator is the minimum of the pension fund's purchases and sales in the past 12 months, and the denominator is the average value of the fund's equity in the past 12 months. Due to large outliers, we winsorize *Turnover* at the 5% level. Values of *Turnover* range from 1% to 128%, with a mean value of 48% and a median of 41%.[9] While fund duration measures the average time a pension fund holds its stocks in the portfolio, *Turnover* tries to capture the percentage of holdings that have changed within the past 12 month. By construction these measures should be inversely related to each other, which is reflected in a negative correlation of 65%. Results presented in Table 5 are consistent with our main results, albeit a bit weaker. On the whole, they confirm that a *High Active share*^{PF} for pension funds is only beneficial if it is accompanied by patience, now measured as pension fund turnover. The slope coefficient of the interaction term is negative and statistically significant for both Fama-French returns. In contrast to our main model, we also find a weak significant (10% level) slope for the Fama-French five factor cross-sectional regression (excluding year and fund fixed effects).

5.3. *Contemporaneous effect on performance*

As mentioned in the introduction, our primary focus is on the ability of activity and patience to predict future fund performance. The contemporaneous relation could be contaminated by various other effects, such as reactions to returns, that we do not aim to analyze. Nevertheless, in this robustness section we also provide results from a contemporaneous regression, defined as:

$$\begin{aligned} R_{i,t} \quad = \quad & \alpha_i + \beta_1 High\ active\ share^{PF}_{i,t} + \beta_2 Duration_{i,t} \\ & + \beta_3 High\ active\ share^{PF}_{i,t} \times Duration_{i,t} + \gamma Controls_{i,t} + \epsilon_{i,t}. \end{aligned} \tag{8}$$

The results in Table 6 show that the significant patterns we have seen so far are not present when we study the contemporaneous relation. In the very short run, pension funds thus seem to react to price movement making the included explanatory variables endogenous.

[9]The unwinsorized turnover measure ranges from 0.1% to 313% with a mean (median) of 50% (40%).

5.4. Control variables and lagged returns

We have also performed several robustness tests on the choice of the control variables used. So far our analysis provides evidence that pension funds that are active and hold their stocks for a longer time period realize, on average, higher gross returns. Of course, the decision making structure of a pension fund is complex and involves not only the management team and the board of directors, but also external advisers, fiduciary managers, and asset managers, all of whom need to be compensated. It is likely that pension funds, which are more active, are also paying more for their asset management, and therefore achieving lower *net* returns for their stakeholders. Unfortunately, information on pension funds' fee structure is only available at an annual frequency from 2012 onwards (while our holdings data starts in April 2009). This reduces our sample size by around 30% and makes computing the net returns difficult. We therefore chose to control for fees paid by including additional variables that capture the pension funds' fee structure to our main regression specifications. Table 7 presents the results. We make use of two different types of fees paid: in Panel A we include total fees paid for equity investment (scaled by end of year assets under management) while in Panel B, we include performance fees paid (scaled by end of year assets under management). Although the fee structure is only available at the annual level, we estimate all regressions on a monthly frequency.

Using this subsample, we confirm our main results, presented above. When we control for fees paid and include fund fixed effects, the coefficient on the interaction term increases by almost 50% (compared to our main results) indicating that, controlling for fees, the result is even stronger. Panels A and B provide evidence that, at least in the cross section, higher fees are correlated with lower gross returns. This finding is in line with the mutual fund literature, which generally reports a negative relationship between fees and performance (Carhart, 1997).

To control for a potentially biased relation between low (high) turnover and high (low) current returns, as documented by Stambaugh (1999), we follow Pástor, Stambaugh, and Taylor (2017) and re-estimate our main regression model by adding $R_{i,t-1}$ and $R_{i,t-2}$ to the set of control variables. Adding past performance to our independent variables slightly lowers the slope coefficient of the interaction term for the Fama-French adjusted returns by 0.134 and 0.08. The estimated pattern for the market-adjusted returns is not in line with our expectations of a positive influence of lagged returns. Including two return lags increases the slope coefficient of the interaction term by 0.06 to 1.053 in the fixed effect model of the market-adjusted returns.

5.5. Out of sample evidence

We conduct an out-of-sample analysis to test how stable the predictive relationship is from an investor's point of view, and to determine whether predictions from the model with the interaction term are significantly better than those from the model without it. Note that our sample window is quite short and, thus, our analysis is likely to produce uncertain results. However, we nevertheless present this evidence to provide a more complete picture. We require at least two years of monthly data to run a regression. Starting in April 2014, for each month we estimate the following full regression model based on past observations only (expanding the window over time):

$$\begin{aligned} R_{i,t} &= \alpha_i + \beta_1 High\ active\ share^{PF}_{i,t-1} + \beta_2 Duration_{i,t-1} \\ &\quad + \beta_3 High\ active\ share^{PF}_{i,t-1} \times Duration_{i,t-1} + \epsilon_{i,t}. \end{aligned} \tag{9}$$

The regression includes fund fixed effects and year fixed effects . Figure 5 presents the time series of slope coefficients and the associated confidence bands at the 5% significance level for each of our three return variables. The estimated coefficients are always positive and, more importantly, the coefficients are also significant (except in the first few months at the beginning of the sample period, most likely due to a shorter estimation window).

In addition to Equation (9), we also estimate the reduced regressions for each month, starting in April 2014. In particular, we estimate the regression model without the interaction term as follows:

$$R_{i,t} = \vartheta_i + \gamma_1 High\ active\ share^{PF}_{i,t-1} + \gamma_2 Duration_{i,t-1} + \epsilon_{i,t}. \tag{10}$$

The one-period ahead forecast error is then given by:

$$\begin{aligned} \hat{\epsilon} &= R_{i,t} - \hat{\alpha}_i - \hat{\beta}_1 High\ active\ share^{PF}_{i,t-1} - \hat{\beta}_2 Duration_{i,t-1} \\ &\quad - \hat{\beta}_3 High\ active\ share^{PF}_{i,t-1} \times Duration_{i,t-1}, \\ \hat{d} &= R_{i,t} - \hat{\vartheta}_i - \hat{\gamma}_1 High\ active\ share^{PF}_{i,t-1} - \hat{\gamma}_2 Duration_{i,t-1}. \end{aligned} \tag{11}$$

Table 9 presents the results of a one sided t-test, which tests $E[\hat{\epsilon}^2 - \hat{f}^2] < 0$ against the null hypothesis of equal means. We reject the null hypothesis of equal means for all three return variables on the 5% or 10% level. For the short sample we analyze, we conclude that including the interaction term into the model reduces the average squared forecast error by 0.5%, 0.2%, and 0.2% for the market adjusted return, the three Fama-French, and the five Fama-French adjusted return, respectively.

6. Conclusions

A gradual increase of assets under management of pension funds worldwide calls for a better understanding of their investment strategies and performance. We use a novel dataset of the asset allocation of Dutch pension funds to provide evidence that pension fund performance is sensitive to fund activity and patience. We measure pension fund activity as *Active share*^{PF}. This is a novel measure, which captures the deviation from the median holdings of the pension funds (the *typical* fund). Patience is measured as stock holding duration or turnover. When we study activity and patience individually, we find no indication of better performance. That is, neither choosing a diverging investment strategy nor taking advantage of a pension fund's long investment horizon is associated with higher returns. However, if we include the interaction of both variables we find that, when pension funds are more active, their performance is only improved if higher activity is accompanied by more patience (i.e., holding assets for a longer period).

Our results are of interest to pension fund boards as well as to supervisors. The former, representing participants, should be interested to see that they can consider pursuing a divergent investment strategy, provided they simultaneously pursue long-term mispricing.

Pension funds do not handle their portfolios themselves. The trustees define long-term goals and then provide one or more asset managers with investment mandates to achieve these goals. Note that we do not have information on the precise mandates of the asset managers employed by the pension funds. Our results, therefore, should not so much be interpreted as pension funds being able to invest in active or patient strategies themselves. Rather, our findings demonstrate that it is the pension fund's ability to draft mandates that incentivize the asset managers to engage in high activity paired with long-term holdings.

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Figures and Tables

Fig. 1. **Active share^{PF} and duration over time.**
The *Active share*^{PF} (left) corresponds to the proportion of the fund's holdings in equities that is different from the median holding in each stock for all pension funds in the sample. *Duration* (right) is defined as the weighted average length of time that a fund has held equities in its portfolio over the last two years. Means, medians, 25^{th}, and 75^{th} percentiles of *Active share*^{PF} and *Duration* across Dutch pension funds are plotted.

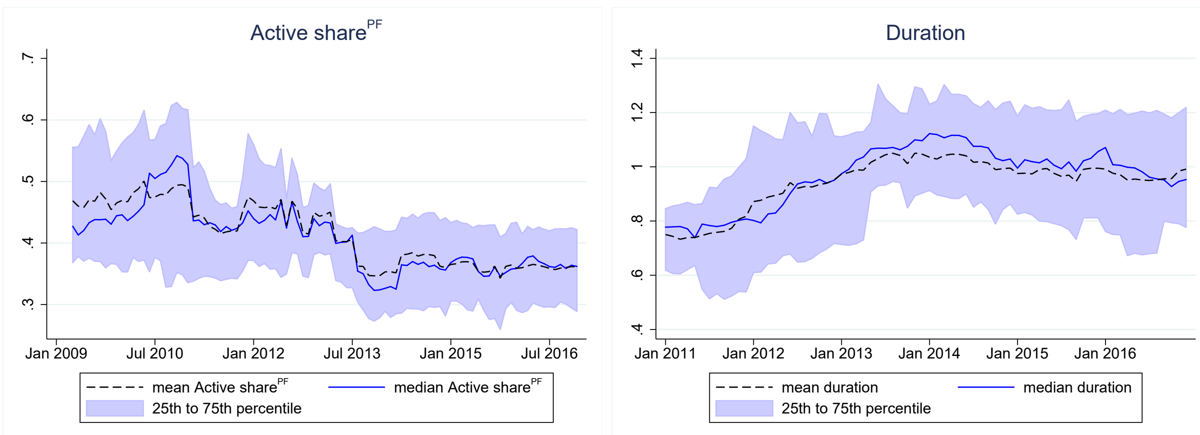

Fig. 2. **Active share^{PF} tercile allocation over time.**
For each of the 39 funds we plot the allocation into *Active share*^{PF} terciles over time. Each row represents one pension fund. The darker the tile the higher the tercile. White tiles represent missing values.

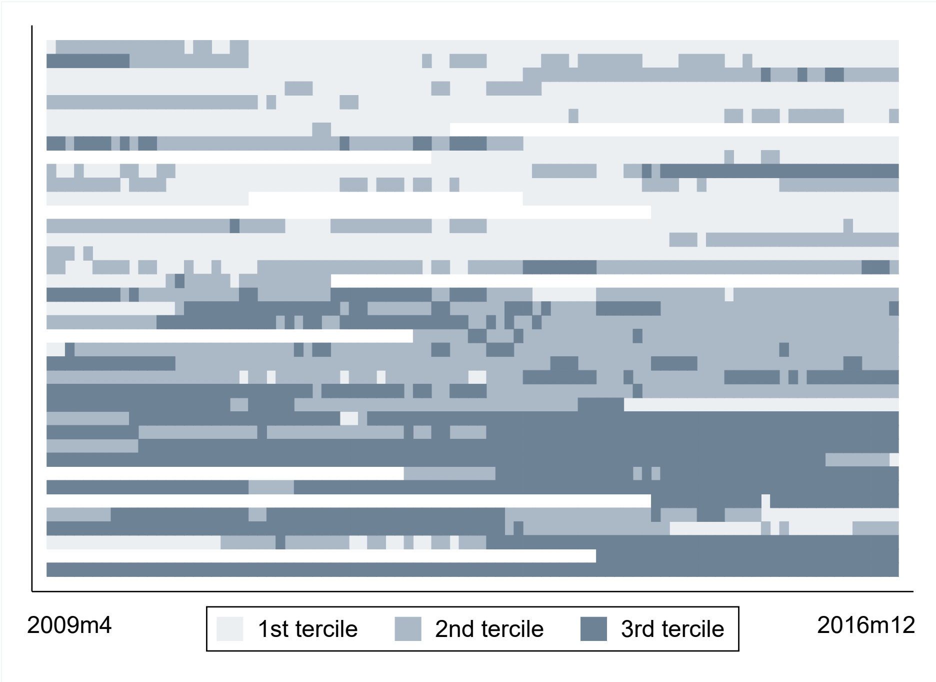

Fig. 3. **Benchmark holdings by geographic region.**
The benchmark fund consists of the median holdings of each ISIN per date. The graph displays the fraction of all non-zero weight stocks per geographic region in the benchmark

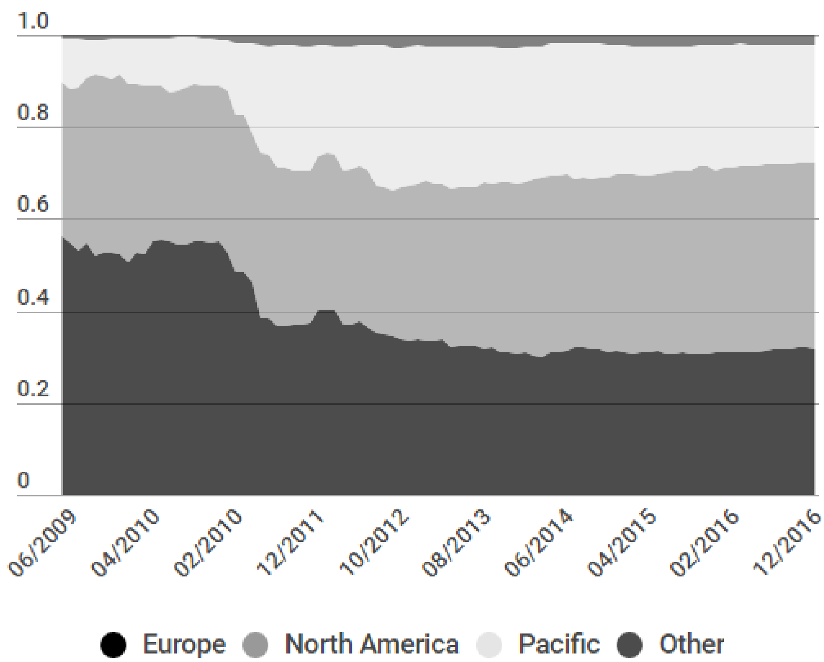

Fig. 4. **Sensitivity of fund performance to patience and duration**
Prediction sensitivity to patience and activity of pension funds from the model without the interaction term (left) and with the interaction term (right).

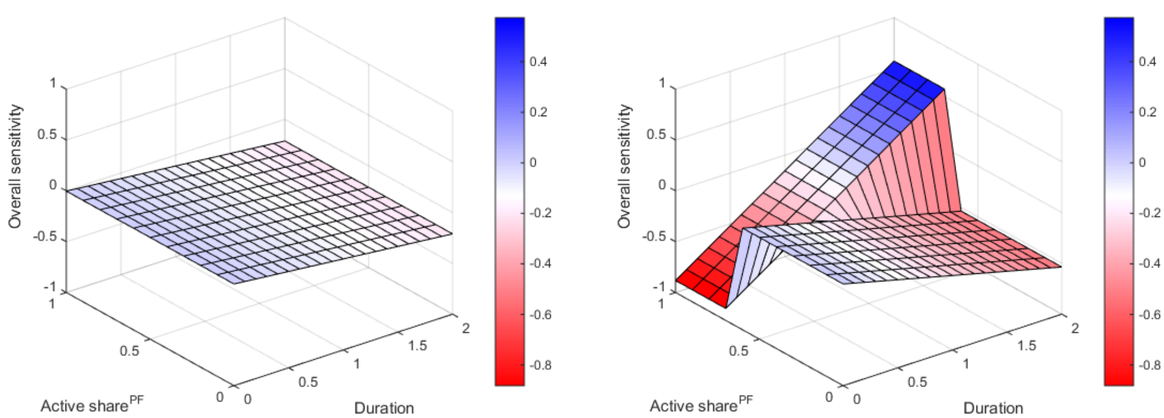

Fig. 5. **Slope of interaction term**

The figure displays estimated slope coefficients of the interaction term based on Equation 9. In each month we regress the return measures on *High Active share*^{PF}, *Duration*, and the interaction of both using past observations only.

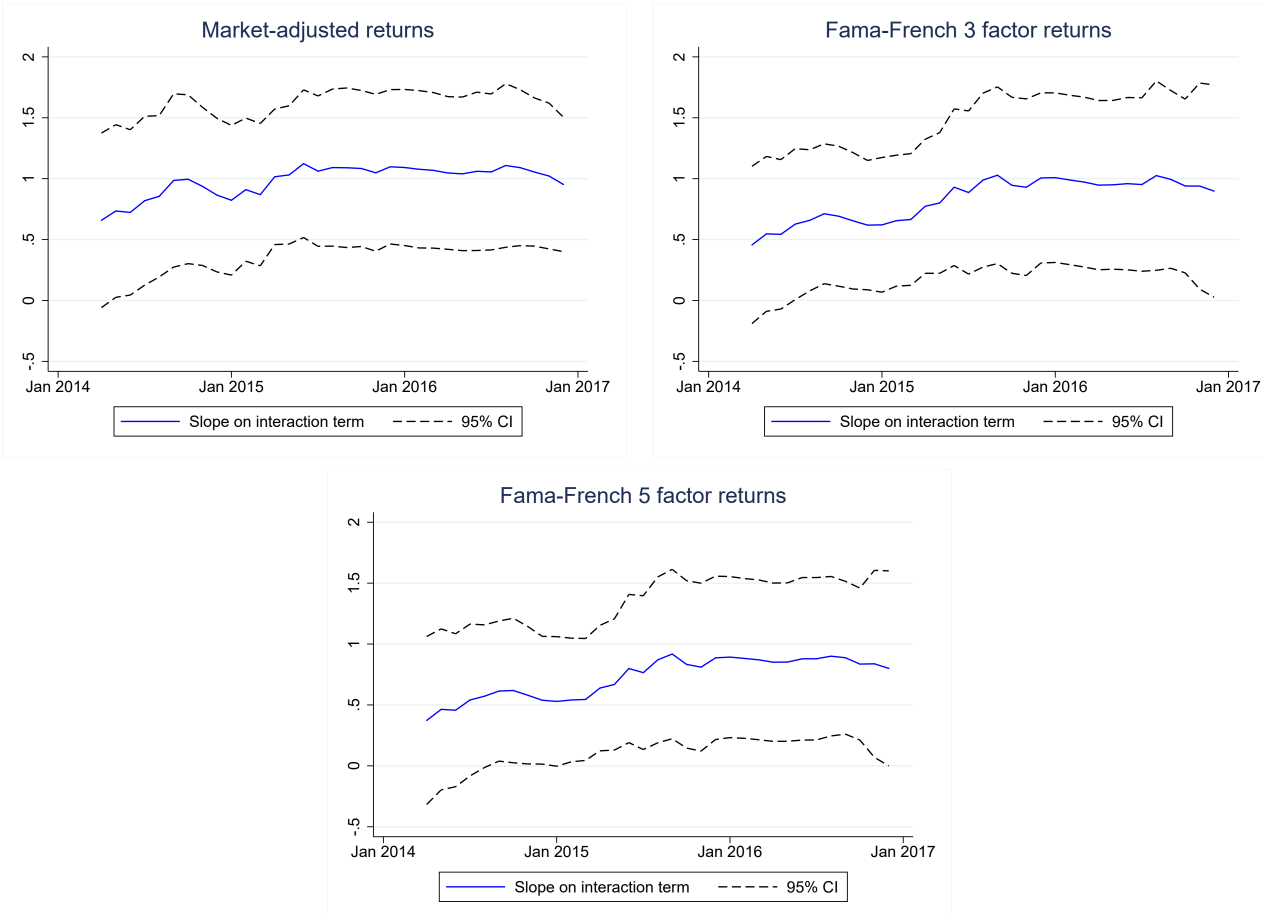

Table 1: **Summary statistics**

The table presents summary statistics of our data and the main variables used in this study. Panel A gives an overview of the sample. Panel B presents our main variables on a monthly frequency and Panel C presents our set of control variables. The control variables are tabulated as end of year values.

Panel A:	
Number of pension funds	39
Number of fund-month obs.	3173
Sample	Apr. 2009 – Dec. 2016

Panel B:	Mean	Median	St. Dev.	Min	Max	Obs.
# stock held per fund-month	1815.0	1586	1335.7	65	6665	3173
# stock held per fund-month with Datastream data	1714.3	1499	1280.2	61	6524	3173
Non-herding share	0.411	0.399	0.134	0.142	0.962	3173
Duration	0.943	0.969	0.339	0.050	1.612	2310
Market-adjusted return	0.000	-0.002	0.027	-0.098	0.131	3166
Fama-French 3 factor return	0.006	0.005	0.024	-0.069	0.108	3173
Fama-French 5 factor return	0.006	0.005	0.024	-0.083	0.107	3173

Panel C: (values as end of year)	Mean	Median	St. Dev.	Min	Max	Obs.
Ratio active to retired participants	1.661	1.274	1.437	0.000	8.271	275
Herfindahl index of age of active participants	0.140	0.134	0.049	0.107	0.603	272
Asset under management (in millions €)	22141	6527	51976	975	366800	270
Equity held (% of AuM)	0.315	0.318	0.081	0.134	0.531	270
Fees (% of AuM)	0.095	0.096	0.049	0.006	0.211	169
Performance fees (% of AuM)	0.005	0.000	0.011	0.000	0.092	169

Table 2: **Correlation table**

The table tabulates the pairwise correlation of the independent variables used in this study.

	AS	Duration	Ln (AuM)	% equity	HI age	Act./Ret.
Active share^{PF}	1.000					
Duration	-0.181^{**}	1.000				
Ln (AuM)	0.102^{*}	0.125^{*}	1.000			
% equity held	0.279^{***}	0.047	0.128^{**}	1.000		
HI age active part.	-0.108^{*}	-0.042	-0.269^{***}	-0.166^{***}	1.000	
Active/Ret. part.	0.008	-0.090	-0.014	0.159^{***}	-0.144^{**}	1.000

Table 3: **Effects of patience and activity on fund performance**

The table presents results from the regression analysis. The dependent variable is the fund monthly return net of the market return (Panel A), adjusted by three Fama-French factors (Panel B) and by five Fama-French factors (Panel C). The independent variables of interest are an indicator variable for high *Active share*^{PF} (third tercile) and a continuous measure of fund duration, and are considered individually and as an interaction term. Both variables are lagged by one month. Control variables include the percentage of equity in the fund's portfolio, the natural logarithm of total investment of the fund, the percentage of active to retired participants in a fund, and the Herfindahl index for the age of active participants. Year and fund fixed effects are included as specified. P-values clustered at fund level are given in parentheses. Level of significance: * 0.10, ** 0.05, *** 0.01.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Panel A: Market-adjusted returns										
High active share^{PF}	0.019	0.046			-0.040	0.002	-0.384*	-0.418***	-0.837**	-0.882***
	(0.826)	(0.669)			(0.627)	(0.988)	(0.092)	(0.004)	(0.023)	(0.002)
Duration			-0.242**	-0.105	-0.249**	-0.105	-0.347***	-0.275***	-0.466**	-0.268*
			(0.028)	(0.446)	(0.027)	(0.457)	(0.005)	(0.005)	(0.022)	(0.082)
High AS× Dur.							0.378	0.494***	0.800*	0.996***
							(0.146)	(0.005)	(0.052)	(0.001)
R^2	0.001	0.052	0.002	0.072	0.002	0.072	0.002	0.066	0.014	0.074
Panel B: 3 Fama-French factor returns										
High active share^{PF}	0.036	0.042			0.000	0.002	-0.204	-0.433**	-0.819	-0.826*
	(0.626)	(0.644)			(0.996)	(0.988)	(0.425)	(0.018)	(0.125)	(0.076)
Duration			-0.129	-0.312*	-0.129	-0.312*	-0.187*	-0.293***	-0.638***	-0.465***
			(0.177)	(0.067)	(0.159)	(0.067)	(0.076)	(0.001)	(0.000)	(0.008)
High AS× Dur.							0.225	0.495**	0.868	0.933**
							(0.394)	(0.014)	(0.111)	(0.049)
R^2	0.001	0.032	0.002	0.043	0.002	0.043	0.002	0.029	0.031	0.045
Panel C: 5 Fama-French factor returns										
High active share^{PF}	0.053	0.037			0.014	0.011	-0.221	-0.375**	-0.722	-0.696
	(0.430)	(0.694)			(0.845)	(0.942)	(0.339)	(0.041)	(0.146)	(0.119)
Duration			-0.113	-0.194	-0.110	-0.192	-0.176**	-0.246***	-0.457***	-0.323**
			(0.162)	(0.220)	(0.149)	(0.224)	(0.039)	(0.001)	(0.005)	(0.044)
High AS× Dur.							0.258	0.432**	0.796	0.795*
							(0.265)	(0.026)	(0.109)	(0.072)
R^2	0.001	0.028	0.001	0.029	0.001	0.029	0.001	0.017	0.020	0.030
Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	N	Y	N	Y	N	Y	N	Y	N	Y
Fund FE	N	Y	N	Y	N	Y	N	N	Y	Y
Clustering	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Obs	3060	3060	2167	2167	2167	2167	2167	2167	2167	2167

Table 4: **Placebo-test**

The table presents results from OLS regressions. The dependent variable is the fund monthly return net of the market return (columns 1-2), adjusted by three Fama-French factors (columns 3-4) and adjusted by five Fama-French factors (columns 5-6). The independent variables of interest are an indicator variable for low *Active share*^{PF} (first tercile) and a continuous measure of fund duration, and are considered individually and as an interaction term. Both variables are lagged by one month. Control variables include the percentage of equity in the fund's portfolio, the natural logarithm of total investment of the fund, the percentage of active to retired participants in a fund, and the Herfindahl index for the age of active participants. Year and fund fixed effects are included as specified. P-values clustered at fund level are given in parentheses. Level of significance: * 0.10, ** 0.05, *** 0.01.

	Market-adj. returns		3 FF factor returns		5 FF factor returns	
Low AS	0.115	0.018	0.013	-0.233	-0.049	-0.241
	(0.621)	(0.941)	(0.949)	(0.325)	(0.762)	(0.307)
Duration	-0.226	-0.068	-0.145	-0.336	-0.132	-0.185
	(0.153)	(0.699)	(0.248)	(0.130)	(0.217)	(0.372)
Low AS × Duration	-0.072	-0.059	0.021	0.115	0.050	0.072
	(0.751)	(0.796)	(0.914)	(0.613)	(0.753)	(0.743)
Controls	Y	Y	Y	Y	Y	Y
Year FE	N	Y	N	Y	N	Y
Fund FE	N	Y	N	Y	N	Y
Clustering	Y	Y	Y	Y	Y	Y
R^2	0.002	0.072	0.002	0.044	0.001	0.029
Obs	2167	2167	2167	2167	2167	2167

Table 5: **SEC Turnover measure, rolling**

The table presents results from OLS regressions. The dependent variable is the fund monthly return net of the market return (columns 1-2), adjusted by three Fama-French factors (columns 3-4) and adjusted by five Fama-French factors (columns 5-6). The independent variables of interest are an indicator variable for high *Active share*^{PF} (third tercile) and a continuous measure of fund turnover, and are considered individually and as an interaction term. Both variables are lagged by one month. Control variables include the percentage of equity in the fund's portfolio, the natural logarithm of total investment of the fund, the percentage of active to retired participants in a fund, and the Herfindahl index for the age of active participants. Year and fund fixed effects are included as specified. P-values clustered at fund level are given in parentheses. Level of significance: * 0.10, ** 0.05, *** 0.01.

	Market-adjusted returns		3 FF factor returns		5 FF factor returns	
High AS	-0.003	0.232	0.090	0.311	0.158	0.317
	(0.987)	(0.314)	(0.495)	(0.143)	(0.158)	(0.116)
Turnover	0.150	-0.129	0.094	0.219	0.189*	0.236
	(0.291)	(0.576)	(0.434)	(0.266)	(0.065)	(0.200)
High AS × Turnover	-0.104	-0.382	-0.216	-0.547*	-0.320*	-0.566*
	(0.664)	(0.269)	(0.238)	(0.089)	(0.056)	(0.083)
Controls	Y	Y	Y	Y	Y	Y
Year FE	N	Y	N	Y	N	Y
Fund FE	N	Y	N	Y	N	Y
Clustering	Y	Y	Y	Y	Y	Y
R^2	0.001	0.045	0.002	0.035	0.001	0.026
Obs	2744	2744	2744	2744	2744	2744

Table 6: **Contemporanous Effect**

The table presents results from a OLS estimates. The dependent variable is the fund monthly return net of the market return (columns 1-2), adjusted by three Fama-French factors (columns 3-4) and adjusted by five Fama-French factors (columns 5-6). The independent variables of interest are an indicator variable for high *Active share*^{PF} (third tercile) and a continuous measure of fund turnover, and are considered individually and as an interaction term. Control variables include the percentage of equity in the fund's portfolio, the natural logarithm of total investment of the fund, the percentage of active to retired participants in a fund, and the Herfindahl index for the age of active participants. Year and fund fixed effects are included as specified. P-values clustered at fund level are given in parentheses. Level of significance: * 0.10, ** 0.05, *** 0.01.

	Market-adj. returns		3 FF factor returns		5 FF factor returns	
High AS	-0.197	-0.598	-0.021	-0.651	-0.018	-0.445
	(0.416)	(0.126)	(0.939)	(0.167)	(0.942)	(0.282)
Duration	-0.287**	-0.432*	-0.036	-0.431	-0.024	-0.259
	(0.018)	(0.066)	(0.747)	(0.169)	(0.793)	(0.387)
High AS × Duration	0.181	0.716*	0.030	0.818*	0.042	0.609
	(0.481)	(0.071)	(0.914)	(0.091)	(0.860)	(0.147)
Controls	Y	Y	Y	Y	Y	Y
Year FE	N	Y	N	Y	N	Y
Fund FE	N	Y	N	Y	N	Y
Clustering	Y	Y	Y	Y	Y	Y
R^2	0.002	0.082	0.002	0.076	0.002	0.054
Obs	2205	2205	2205	2205	2205	2205

Table 7: **Controlling for fees**

The table presents results from OLS regressions. The dependent variable is the fund monthly return net of the market return (columns 1-2), adjusted by three Fama-French factors (columns 3-4) and adjusted by five Fama-French factors (column 5-6). The independent variables of interest are an indicator variable for high *Active share*^{PF} (third tercile) and a continuous measure of fund turnover, and are considered individually and as an interaction term. Both variables are lagged by one month. Control variables include the percentage of equity in the fund's portfolio, the natural logarithm of total investment of the fund, the percentage of active to retired participants in a fund, and the Herfindahl index for the age of active participants. Panel A includes a variable capturing total fees paid for equity management (divided by end of year assets under management) and Panel B includes a variable measuring performance fees (divided by end of year assets under management). Year and fund fixed effects are included as specified. P-values clustered at fund level are given in parentheses. Level of significance: * 0.10, ** 0.05, *** 0.01.

Panel A:						
	Market-adj. returns		3 FF factor returns		5 FF factor returns	
High AS	-0.475	-1.218***	-0.244	-1.041	-0.228	-1.057
	(0.174)	(0.003)	(0.478)	(0.172)	(0.497)	(0.160)
Duration	-0.182	-0.211	-0.301**	-0.421	-0.273**	-0.285
	(0.343)	(0.317)	(0.037)	(0.167)	(0.015)	(0.350)
High AS × Duration	0.353	1.348***	0.248	1.325*	0.255	1.354*
	(0.317)	(0.003)	(0.458)	(0.084)	(0.428)	(0.063)
(Equity fees/AuM) × 100	2.830**	2.050	-0.178	0.611	-0.756	-0.241
	(0.034)	(0.247)	(0.877)	(0.792)	(0.446)	(0.904)
R^2	0.005	0.104	0.002	0.071	0.002	0.051
Panel B:						
	Market-adj. returns		3 FF factor returns		5 FF factor returns	
High AS	-0.365	-1.203***	-0.271	-1.038	-0.274	-1.061
	(0.224)	(0.003)	(0.414)	(0.181)	(0.401)	(0.164)
Duration	-0.315*	-0.212	-0.317**	-0.432	-0.258**	-0.296
	(0.061)	(0.306)	(0.025)	(0.157)	(0.031)	(0.339)
High AS × Duration	0.325	1.339***	0.263	1.314*	0.274	1.346*
	(0.311)	(0.003)	(0.427)	(0.088)	(0.391)	(0.065)
(Perf. fees/AuM) × 100	-0.786	7.606	-4.427***	10.570	-3.624**	8.706
	(0.857)	(0.169)	(0.007)	(0.199)	(0.015)	(0.196)
R^2	0.003	0.104	0.003	0.072	0.002	0.051
Controls	Y	Y	Y	Y	Y	Y
Year FE	N	Y	N	Y	N	Y
Fund FE	N	Y	N	Y	N	Y
Clustering	Y	Y	Y	Y	Y	Y
Obs	1539	1539	1539	1539	1539	1539

Table 8: **Including lagged return variables**

The table presents results from OLS regressions.The dependent variable is the fund monthly return net of the market return (columns 1-2), adjusted by three Fama-French factors (columns 3-4) and adjusted by five Fama-French factors (columns 5-6). The independent variables of interest are an indicator variable for high *Active share*^{PF} (third tercile) and a continuous measure of fund duration, and are considered individually and as an interaction term. Control variables include the two lags of the return variables, the percentage of equity in the fund's portfolio, the natural logarithm of total investment of the fund, the percentage of active to retired participants in a fund, and the Herfindahl index for the age of active participants. Year and fund fixed effects are included as specified. P-values clustered at fund level are given in parentheses. Level of significance: * 0.10, ** 0.05, *** 0.01.

	Market-adj. returns		3 FF factor returns		5 FF factor returns	
High AS	-0.365*	-0.921***	-0.177	-0.719*	-0.204	-0.641
	(0.099)	(0.003)	(0.404)	(0.063)	(0.308)	(0.102)
Duration	-0.348***	-0.324*	-0.169*	-0.379***	-0.165**	-0.277**
	(0.004)	(0.065)	(0.058)	(0.004)	(0.028)	(0.026)
High AS × Duration	0.360	1.053***	0.193	0.799**	0.236	0.715*
	(0.157)	(0.001)	(0.377)	(0.043)	(0.241)	(0.067)
Market-adj. returns (t-1)	-0.109***	-0.189***				
	(0.000)	(0.000)				
Market-adj. returns (t-2)	0.191***	0.131***				
	(0.000)	(0.000)				
3 FF factor returns (t-1)			0.192***	0.173***		
			(0.000)	(0.000)		
3 FF factor returns (t-2)			0.012	0.007		
			(0.281)	(0.509)		
5 FF factor returns (t-1)					0.175***	0.164***
					(0.000)	(0.000)
5 FF factor returns (t-2)					-0.012	-0.016
					(0.321)	(0.171)
Controls	Y	Y	Y	Y	Y	Y
Year FE	N	Y	N	Y	N	Y
Fund FE	N	Y	N	Y	N	Y
Clustering	Y	Y	Y	Y	Y	Y
R^2	0.056	0.131	0.039	0.073	0.031	0.055
Obs	2167	2167	2167	2167	2167	2167

Table 9: **Out of sample evidence**

The table presents results from one-sided t-tests for differences in mean. $\hat{\epsilon}^2$ are the squared residuals from Equation 9 and $\hat{f}^2$ are the squared residuals based on Equation 10. Variables are explained in Section 5. Level of significance: * 0.10, ** 0.05, *** 0.01.

	Mean $\hat{\epsilon}^2$	Mean $\hat{f}^2$	Difference	p-value one sided t-test
Market-adj. return	9.496	9.527	-0.031	0.047 **
3 FF factor return	9.166	9.189	-0.023	0.066 *
5 FF factor return	9.065	9.085	-0.020	0.060 *

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