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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 typical pension fund behavior, and b) whether the pension fund is patient in exploiting investment 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 increases its duration by one standard deviation, annual returns tend to increase by 2.3%. Our findings indicate that some pension funds are patient enough to exploit long-term investment opportunities.

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1. Introduction

Pension funds provide the main source of income for the retired and elderly. 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. This has resulted in, among other things, widespread benefit cuts. It is therefore of great importance to un-

derstand 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 typically save for 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 investment 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 are patient in their investment strategies (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

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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 et al., 2016; Koetsier and Bikker, 2017; Koetsier and Bikker, 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 investment 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 et al., 2015).

The active share measure we introduce can capture two channels of non-herding behavior: asset allocation and stock picking. First, *Active share*^{PF} could increase because a fund invests in an equity market that the other pension funds do not include in their strategic asset allocation. For example, if a pension fund invests in emerging markets while the majority of other pension funds shun away from emerging markets, this particular fund will end up with a higher *Active share*^{PF} measure. Second, if a pension fund engages in security picking within a specific equity market, its active share will go up as well. We see both these channels as forms of non-herding behavior. Although classifying asset allocation as “activity” might be slightly confusing to some, we decided to use this name to align our measure with Cremers and Petajisto (2009).

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 extend their analysis and analyze whether a similar effect can be found for the arguably more patient pension funds, in particular in the established Dutch pension fund market. In contrast to mutual funds, pension funds have in general a more complex objective function. Pension funds do not only have to maximize returns given a certain risk profile (as mutual funds usually do), they also have to account for their participant structure (the term structure of future payouts) and are subject to a higher degree of supervision from the central bank. These additional institutional factors are likely to have an influence on a pension fund's equity allocation and thus on its *Active share*^{PF} and fund holding duration. We therefore posit that the pension fund market is an interesting setting to test whether activity and duration also influence pension fund equity returns.

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 investment 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 et al. (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 a favorable environment to examine funds' investment performance. The Dutch pension system is made up of three pillars; a pay-as-you-go scheme which is funded through social security contributions of the working population, occupational pension funds (mandatory joint contributions from employers and employees), and private pension schemes. The system of occupational pension funds 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 in our sample period. The funds' investment behavior is thus not disturbed by fire-sales. We focus on the 39 largest occupational pension funds for which we can track the monthly asset allocation at the individual security (ISIN) level. This detailed dataset covers more than 80% of all pension fund assets and lists 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 et al. (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 et al. (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 et al., 1993; Blake et al., 1999; Aglietta et al., 2012) 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 et al., 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 et al. (2012) stress that the age of pension fund participants is a crucial indicator for the fund's asset allocation. Andonov et al. (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, mar-

ket timing, and security selection. Broeders and de Haan (2019) extend this line of research using regulatory reports of Dutch pension funds and point to the importance of benchmark 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 et al., 2016 and de Haan and Kakes, 2011 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

$$Active\ share_{i,t}^{PF} = \frac{1}{2} \sum_{j \in Q_{i,t}} |w_{i,j,t} - w_{median,j,t}| \quad (1)$$

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 instead of the mean weights as the benchmark for the following reasons. 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 only for those funds that do hold this specific asset. It is particularly this type of fund behavior that we aim to capture. Second, the median weights are less sensitive to changes in any specific funds. As we have only 39 funds in the empirical part, the reference fund based on average weights might be too sensitive to extreme weights (most likely by relatively small funds). We therefore think that the median weights are a more reliable measure.

Our active share measure can capture two channels of non-herding behavior: asset allocation and stock picking. In both cases, *Active share*^{PF} increases if a pension fund invests in an asset which

is held by less than half of the pension funds in our universe. First, through the asset allocation channel, *Active share*^{PF} could increase because a fund invests in an equity market that the other pension funds do not include in their strategic asset allocation. For example, if a pension funds invests in emerging markets while the majority of other pension funds shun away from emerging markets, this particular fund will end up with a higher *Active share*^{PF} measure. Second, if a pension fund engages in security picking within a specific equity market, its active share will go up as well. We see both these channels as forms of non-herding behavior. Although classifying asset allocation as “activity” might be slightly confusing to some, we stick to this name to align our measure with Cremers and Petajisto (2009).

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

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

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 $\alpha_{i,j,t}$, 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:

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

We 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 investment 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

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

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

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 the 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:

$$R_{i,t} = \alpha_i + \beta_1 \text{High active share}_{i,t-1}^{\text{PF}} + \beta_2 \text{Duration}_{i,t-1} + \beta_3 \text{High active share}_{i,t-1}^{\text{PF}} \times \text{Duration}_{i,t-1} + \gamma \text{Controls}_{i,t-1} + \epsilon_{i,t}. \quad (6)$$

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 *Active share*^{PF} and *Duration* measures, 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 (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 at the 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 – the start of the reporting requirement – until December 2016. As we need two years of data to calculate the duration measure, the regression analysis is restricted to the month starting from April 2011 onwards.

For two funds in our sample, ABP and Zorg en Welzijn², 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.³

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).

To control for the exposure to various recognized risk factors we calculate risk-adjusted returns. First, for each fund-month observation we calculate the value-weighted equity return of each pension fund based on all ISINs for which stock price data is available. The fund return net of the market return is the difference between the pension fund return and the 'Fama-French' global market factor. In addition, we calculate the factor loadings of each fund to the three or five global 'Fama-French'-factors, and the factor exposure as a product of the factor loading and the current factor

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

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

³ The results of our analysis are robust to including an indicator variable in our regression analysis to flag the pension funds involved. The results can be found in the Internet Appendix (Table A1).

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.

<i>Panel A:</i>						
Number of pension funds					39	
Number of fund-month obs.					3173	
Sample	Apr. 2009 –	Dec. 2016				
<i>Panel B:</i>	Mean	Median	St. Dev.	Min	Max	Obs.
# stock held per fund-month	1746.7	1566	1294.6	64	6522	3173
# stock held per fund-month with Datastream data	1665.3	1480	1246.4	60	6417	3173
Active share ^{PF}	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	0.028	−0.099	0.132	3166
Fama-French 3 factor return	0.004	0.003	0.022	−0.062	0.101	3173
Fama-French 5 factor return	0.005	0.004	0.021	−0.066	0.110	3173
<i>Panel C: (values as end of year)</i>	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 €)	22,141	6527	51,976	975	366,800	270
Equity held (% of AuM)	31.5	31.8	8.1	13.4	53.1	270
Fees (% of AuM)	0.090	0.092	0.047	0.006	0.203	177
Performance fees (% of AuM)	0.005	0.000	0.010	0.000	0.078	177

value.⁴ The risk-adjusted returns are given by the difference between the fund return and the sum of all factor exposures.⁵

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, yielding 3173 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. Note that the non-overlapping behavior can arise from a different security selection within a specific equity market or from a different strategic asset allocation strategy in which funds focus on a different market. 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 1746. The number of stocks held in the portfolio varies significantly from 64 to 6522 stocks.

On average, market data is available in Datastream for more than 95% of the stocks reported. The average monthly fund return net of the market return is 0.01%, which results in an annualized average return of 0.17%. If we adjust the fund returns by the global three or five Fama-French factors⁶, the average pension fund risk-adjusted return takes a value of 0.4% per month.

Finally, in Panel C of Table 1 we report the pension fund characteristics that we use as control variables in our multivariate re-

gressions. 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,⁷ varies widely between the funds in our sample, ranging from 0.1 to 0.6.⁸ This heterogeneous group of funds provides an interesting 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 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 1120 (median 1197) different stocks ranging from 389 at the beginning of our sample period to 1597 in later months (i.e., stocks that have a non-zero median weight). Note, that the median weights are an artificially-constructed fund and the sum of its weights per time period does not need to be equal to 1. Indeed, the average sum of weights for our dataset is 1.27.

Fig. 1 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

⁴ Factors are provided by Kenneth French. See http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html. Sensitivities to factors are calculated based on the full sample. We also repeated the estimation with a rolling window of two years approach at the stock level and the results remain very similar, see Table A9 in the Internet Appendix.

⁵ Stock price data is converted into euro prices before the returns are calculated. The Fama-French factors are converted to euro returns using the following formula: $ret_{eur,t} = (1 + ret_{dollar,t})(1 + \frac{x_t - x_{t-1}}{x_{t-1}}) - 1$ with x_t being the exchange rate EUR/USD at time t .

⁶ See Fama and French (1993) and Fama and French (2016) for 3 and 5 factors, respectively.

⁷ 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*.

⁸ 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%.

Fig. 1. 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.

Pacific region (Japan, Australian, New Zealand, Singapore etc.). Of note, 97% of the stocks in the benchmark are developed market stocks.⁹

In the previous section we discussed that the *Active share*^{PF} measure might capture two channels of non-herding behavior. To distinguish between them, we look at the weight and *Active share*^{PF} decomposition based on geographic regions. If strategic asset allocation would be an irrelevant determinant of *Active share*^{PF} then the distribution of *Active share*^{PF} should be independent of the typical strategic choices such as the regional allocation. In Fig. 2 we report weight decomposition based on geographic regions for high *Active share*^{PF} and non-high *Active share*^{PF} pension funds. We find that high *Active share*^{PF} funds tend to invest less in Europe and more in 'Other' (which includes among other countries in the Middle East, Africa and South and Central America) than non-active pension funds, but this pattern disappears at the end of our period. Moreover, in Fig. 3 we look at the *Active share*^{PF} decomposition based on geographic regions (i.e., the fraction of *Active share*^{PF} generated in each geographic region), to see whether it is in line with the weight decomposition. Although European assets cover more than 42% of all assets on average, they are responsible for only 38% of the fund activity. On the other hand, weights for assets classified as 'Other' cover only 9% in weights, but corresponds to 11% in the activity measure. A similar increase of 2 percentage points can be observed for assets from the Pacific region.

Following Kacperczyk et al. (2014) we also check whether high *Active share*^{PF} pension funds outperform during recession or expansion periods which can indicate better stock picking or market-timing abilities.¹⁰ The high *Active share*^{PF} pension funds perform – on average – better than their peers during recession (difference of the average market-adjusted returns is 0.164%) and expansion periods (difference of 0.026%). We take this as an indication that these funds are both: good stock pickers but also good market timers. The higher difference in returns during recession periods suggests that effects from better stock picking ability are stronger. Taking all of this together, we conclude that the relative importance of strate-

gic asset allocation compared to stock picking is not clear cut and seems to vary over time.

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 (a negative 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 Fig. 4, 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 a 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 75th percentile and 25th 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.

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;¹¹ 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.

Fig. 5 plots the *Active share*^{PF}-tercile allocation of each fund over time. Clearly, our overall sample consists 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

⁹ We follow the MSCI classifications with regard to geographic region and market type.

¹⁰ We thank an anonymous referee for pointing us towards this paper. We use the Recession Indicator Series from FRED, Federal Reserve Bank of St. Louis.

¹¹ We decided to model activity as a dummy variable based on *Active share*^{PF} to allow for a non-linear relationship to performance.

Fig. 2. Weight geographic decomposition for high $Active\ share^{PF}$ pension funds and not-high $Active\ share^{PF}$ pension funds. The figure displays the average asset weight per geographic region in the high $Active\ share^{PF}$ funds (left) and in the non-high $Active\ share^{PF}$ pension funds (right).

Fig. 3. Weight and $Active\ share^{PF}$ regional decomposition. The figure displays the average asset weight per geographic region (left) and the average fraction of $Active\ share^{PF}$ per geographic region (right) of all pension funds in our sample.

Table 2

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

	AS^{PF}	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

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 fund 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 accompa-

nied with a significant change in the performance of the fund (the time-series effect).¹²

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 compari-

¹² Following Cremers and Pareek (2016) we also confirm the robustness of our main result to a seven factor model including the factors *Betting against Beta* which is a long-short portfolio in high and low beta stocks (Frazzini and Pedersen, 2014) and *Quality minus Junk* which was introduced in Asness et al. (2017). The results are presented in Table A2 in the Internet Appendix.

Fig. 4. 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 period that a fund has held equities in its portfolio over the last two years. Means, medians, 25th, and 75th percentiles of Active share^{PF} and Duration across Dutch pension funds are shown.

Fig. 5. 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.

son. 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.

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, con-

trol 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 with year fixed effects (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 investment opportunities, 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

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}	0.018 (0.835)	0.047 (0.665)			−0.041 (0.624)	0.004 (0.978)	−0.381 (0.101)	−0.424*** (0.004)	−0.852** (0.023)	−0.902*** (0.002)
Duration			−0.243** (0.029)	−0.106 (0.452)	−0.250** (0.028)	−0.105 (0.465)	−0.347*** (0.006)	−0.276*** (0.005)	−0.484** (0.019)	−0.272* (0.083)
High AS × Dur.							0.374 (0.158)	0.501*** (0.005)	0.816* (0.050)	1.020*** (0.001)
R ²	0.001	0.052	0.002	0.071	0.002	0.071	0.002	0.066	0.014	0.073
Panel B: 3 Fama-French factor returns										
High active share ^{PF}	0.023 (0.749)	0.054 (0.536)			0.018 (0.797)	0.043 (0.721)	−0.426** (0.034)	−0.486*** (0.001)	−0.899*** (0.005)	−0.770** (0.021)
Duration			−0.088 (0.364)	−0.233 (0.108)	−0.085 (0.375)	−0.226 (0.123)	−0.210* (0.072)	−0.319*** (0.002)	−0.304* (0.070)	−0.376** (0.013)
High AS × Dur.							0.489** (0.036)	0.579*** (0.002)	1.009*** (0.006)	0.915** (0.016)
R ²	0.001	0.047	0.001	0.042	0.002	0.042	0.003	0.029	0.024	0.044
Panel C: 5 Fama-French factor returns										
High active share ^{PF}	0.009 (0.893)	0.060 (0.428)			0.000 (0.997)	0.021 (0.859)	−0.326 (0.138)	−0.403** (0.011)	−0.962*** (0.001)	−0.794*** (0.010)
Duration			−0.074 (0.438)	−0.222 (0.116)	−0.074 (0.431)	−0.219 (0.125)	−0.166 (0.120)	−0.318*** (0.001)	−0.262* (0.079)	−0.369** (0.010)
High AS × Dur.							0.359 (0.131)	0.453** (0.014)	1.083*** (0.001)	0.918*** (0.008)
R ²	0.001	0.051	0.001	0.037	0.001	0.037	0.002	0.023	0.026	0.039
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

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 increases its duration by one standard deviation, and if this fund is also active, then the fund is rewarded with a 2.3% higher return (annualized). If the pension fund is not active, however, the increase in duration is accompanied by a 1.5% drop in the return.

Fig. 6 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.¹³

To better understand the drivers of our results we also split the sample along different dimensions. Dividing pension funds into small and large funds (based on assets under management, split at the median) we find stronger results for large funds. We also split the sample into funds with a high percentage of assets invested in equity and their counterparts. Again, we find our main effect to be present for funds with a higher equity share. In both cases our findings are consistent with our expectations that larger funds and funds which invest a higher fraction of their assets in equity are more prone to the documented effect. Lastly, we split the sample into young and old funds (based on the funds' participant structure) and find results for funds with a higher active participants to retired participant ratio. We provide results for all splits in the Internet Appendix (Tables A3, A4, and A5).

To mitigate concerns that high *Active share*^{PF} is only driven by the number of stocks in a pension funds portfolio we substitute high *Active share*^{PF} by *high number of stocks* (an indicator variable equal to one if the number of stocks the fund is invested in is in the highest tercile in a given month). The results are presented in Table A6. We do not find any significant results here. We also run our main regression in which we additionally control for the number of stocks. Our results remain robust (Table A7).

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).

¹³ To support evidence that sensitivity to duration is different for funds with high activity and low activity we also estimate the regression only with duration for the highest tercile and for the two lowest tercile separately. We report the results in Table A8. Signs in all cases are as we expected – positive for the third tercile and negative for the first two terciles.

Fig. 6. 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).

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	0.114 (0.629)	0.019 (0.941)	0.062 (0.776)	−0.244 (0.259)	0.036 (0.871)	−0.140 (0.540)
Duration	−0.228 (0.155)	−0.067 (0.706)	−0.062 (0.635)	−0.272 (0.138)	−0.061 (0.632)	−0.218 (0.232)
Low AS × Duration	−0.071 (0.759)	−0.060 (0.797)	−0.068 (0.750)	0.141 (0.484)	−0.036 (0.868)	0.043 (0.840)
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
<i>R</i> ²	0.002	0.071	0.002	0.043	0.001	0.038
Obs	2167	2167	2167	2167	2167	2167

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 pension 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 investment opportunities.

5.2. Different cut-off values for High *Active share*^{PF}

The regression specifications with fund fixed effect rely on funds to switch between *High Active share*^{PF} (third tercile) and low and medium active share (first and second tercile). For 26 of the funds in our sample the *High Active share*^{PF} indicator variable takes both values, zero and one. To mitigate concerns that the estimated coefficients are sensitive to the cut-off values, we re-estimated our main results using different thresholds for the *High Active share*^{PF} indicator variable. We split the sample at the median and at the third quartile. We provide the corresponding results in the Table 5. The findings remain robust to different cut-off values.

5.3. 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

Table 5

Different thresholds for high active share. 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). In Panel A, the independent variables of interest are an indicator variable for high *Active share*^{PF} (higher than median) and a continuous measure of fund duration, and are considered individually and as an interaction term. Both variables are lagged by one month. In Panel B, the independent variables of interest are an indicator variable for high *Active share*^{PF} (fourth quartile) 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 *P*-values clustered at fund level are given in parentheses. Level of significance: * 0.10, ** 0.05, *** 0.01.

Panel A: Median						
	Market-adj. returns		3 FF factor returns		5 FF factor returns	
High AS	−0.465 (0.137)	−0.898*** (0.004)	−0.526* (0.090)	−0.799** (0.014)	−0.513 (0.125)	−0.873*** (0.008)
Duration	−0.442*** (0.001)	−0.410** (0.036)	−0.323** (0.026)	−0.509** (0.015)	−0.300** (0.033)	−0.521*** (0.006)
High AS × Duration	0.442 (0.162)	0.970*** (0.003)	0.553* (0.072)	0.911*** (0.008)	0.525 (0.111)	0.974*** (0.005)
R ²	0.003	0.074	0.003	0.045	0.003	0.041
Panel B: Quartile						
High AS	−0.499* (0.062)	−0.977** (0.024)	−0.631** (0.016)	−0.970** (0.037)	−0.535* (0.073)	−1.004** (0.027)
Duration	−0.341*** (0.008)	−0.250* (0.093)	−0.216* (0.062)	−0.375** (0.016)	−0.180 (0.104)	−0.368** (0.016)
High AS × Duration	0.515* (0.067)	1.135*** (0.008)	0.686*** (0.009)	1.121** (0.012)	0.556* (0.053)	1.139*** (0.008)
R ²	0.003	0.073	0.003	0.045	0.002	0.040
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	2167	2167	2167	2167	2167	2167

defined as

$$Turnover_{i,t-1} = \frac{\min(buys_{i,t-1}, sells_{i,t-1})}{\text{avg}(\text{total assets}_{i,t-1})} \quad (7)$$

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%.¹⁴ 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 6 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 by a lower value of 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).

5.4. 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:

$$R_{i,t} = \alpha_i + \beta_1 \text{High active share}_{i,t}^{\text{PF}} + \beta_2 \text{Duration}_{i,t} + \beta_3 \text{High active share}_{i,t}^{\text{PF}} \times \text{Duration}_{i,t} + \gamma \text{Controls}_{i,t} + \epsilon_{i,t}. \quad (8)$$

The results in Table 7 show that the significant patterns we have seen so far are also present when we study the contemporaneous relation. However, in the very short run pension funds might react to price movement making the included explanatory variables endogenous and not clear how the pure effect can be identified.

5.5. 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 and present the results in Table 8. 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

¹⁴ The unwinsorized turnover measure ranges from 0.1% to 313% with a mean (median) of 50% (40%).

Table 6

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-adj. returns		3 FF factor returns		5 FF factor returns	
High AS	−0.006 (0.972)	0.240 (0.304)	0.140 (0.286)	0.399** (0.044)	0.017 (0.881)	0.333* (0.066)
Turnover	0.150 (0.297)	−0.131 (0.576)	0.242** (0.034)	0.135 (0.466)	0.250* (0.052)	0.152 (0.407)
High AS × Turnover	−0.100 (0.680)	−0.395 (0.261)	−0.321* (0.052)	−0.600** (0.016)	−0.103 (0.550)	−0.483** (0.034)
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
<i>R</i> ²	0.001	0.045	0.002	0.050	0.002	0.055
Obs	2744	2744	2744	2744	2744	2744

Table 7

Contemporaneous 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	−0.190 (0.440)	−0.612 (0.126)	−0.315 (0.171)	−0.682* (0.084)	−0.229 (0.367)	−0.709* (0.059)
Duration	−0.285** (0.020)	−0.439* (0.067)	−0.106 (0.334)	−0.411 (0.117)	−0.061 (0.564)	−0.409 (0.116)
High AS × Duration	0.173 (0.508)	0.734* (0.070)	0.363 (0.131)	0.867** (0.040)	0.241 (0.334)	0.871** (0.028)
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
<i>R</i> ²	0.002	0.081	0.002	0.075	0.002	0.071
Obs	2205	2205	2205	2205	2205	2205

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 et al. (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 (see Table 9). Adding past performance to our independent variables slightly lowers the slope coefficient of the interaction term for the Fama-French adjusted returns, however, they stay significant. 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 1.080 in the fixed effect model of the market-adjusted returns.

5.6. 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 five 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):

$$R_{i,t} = \alpha_i + \beta_1 \text{High active share}_{i,t-1}^{\text{PF}} + \beta_2 \text{Duration}_{i,t-1} + \beta_3 \text{High active share}_{i,t-1}^{\text{PF}} \times \text{Duration}_{i,t-1} + \epsilon_{i,t}. \quad (9)$$

Table 8

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	−0.470 (0.184)	−1.230*** (0.003)	−0.585** (0.020)	−1.264*** (0.008)	−0.455* (0.082)	−1.228*** (0.008)
Duration	−0.183 (0.347)	−0.214 (0.316)	−0.297** (0.045)	−0.371 (0.112)	−0.315** (0.026)	−0.366* (0.097)
High AS × Duration	0.347 (0.332)	1.363*** (0.003)	0.580** (0.035)	1.554*** (0.005)	0.433 (0.119)	1.494*** (0.005)
(Equity fees/AuM) × 100	2.853** (0.036)	2.073 (0.247)	1.007 (0.341)	1.539 (0.438)	0.665 (0.498)	1.607 (0.392)
R ²	0.005	0.103	0.003	0.062	0.003	0.053
Panel B:						
	Market-adj. returns		3 FF factor returns		5 FF factor returns	
High AS	−0.360 (0.236)	−1.215*** (0.003)	−0.551** (0.017)	−1.253*** (0.010)	−0.435* (0.083)	−1.217*** (0.009)
Duration	−0.318* (0.060)	−0.216 (0.306)	−0.350** (0.013)	−0.374* (0.100)	−0.353*** (0.009)	−0.369* (0.086)
High AS × Duration	0.319 (0.326)	1.354*** (0.003)	0.573** (0.031)	1.546*** (0.005)	0.430 (0.115)	1.485*** (0.005)
(Perf. fees/AuM) × 100	−0.996 (0.822)	7.720 (0.170)	−1.249 (0.616)	7.359 (0.252)	−1.442 (0.506)	7.664 (0.213)
R ²	0.003	0.103	0.003	0.063	0.003	0.053
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 9

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	−0.363 (0.109)	−0.943*** (0.003)	−0.356** (0.034)	−0.698** (0.021)	−0.257 (0.140)	−0.686** (0.011)
Duration	−0.349*** (0.004)	−0.329* (0.066)	−0.192* (0.055)	−0.330** (0.016)	−0.152* (0.086)	−0.304** (0.012)
High AS × Duration	0.356 (0.169)	1.080*** (0.001)	0.411** (0.039)	0.839** (0.016)	0.287 (0.137)	0.805*** (0.009)
Market-adj. returns (<i>t</i> − 1)	−0.111*** (0.000)	−0.189*** (0.000)				
Market-adj. returns (<i>t</i> − 2)	0.190*** (0.000)	0.131*** (0.000)				
3 FF factor returns (<i>t</i> − 1)			0.065*** (0.000)	0.025* (0.064)		
3 FF factor returns (<i>t</i> − 2)			0.113*** (0.000)	0.082*** (0.000)		
5 FF factor returns (<i>t</i> − 1)					0.076*** (0.000)	0.042*** (0.001)
5 FF factor returns (<i>t</i> − 2)					0.131*** (0.000)	0.101*** (0.000)
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	0.021	0.051	0.026	0.050
Obs	2167	2167	2167	2167	2167	2167

Fig. 7. Slope of interaction term. The figure displays estimated slope coefficients of the interaction term based on Eq. (9). In each month we regress the return measures on *High Active share^{PF}*, *Duration*, and the interaction of both using past observations only.

The regression includes fund fixed effects and year fixed effects. Fig. 7 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 Eq. (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:

$$R_{i,t} = \vartheta_i + \gamma_1 \text{High active share}_{i,t-1}^{\text{PF}} + \gamma_2 \text{Duration}_{i,t-1} + \epsilon_{i,t}. \quad (10)$$

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

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

Table 10 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 0.33%, 0.25%, and 0.26% for the market adjusted return, the three Fama-French, and the five Fama-French adjusted return, respectively.

Table 10

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 Eq. (9) and $\hat{f}^2$ are the squared residuals based on Eq. (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 <i>t</i> -test
Market-adj. return	9.840	9.873	−0.033	0.047 **
3 FF factor return	8.927	8.949	−0.022	0.044 **
5 FF factor return	8.673	8.697	−0.023	0.034 **

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 superior 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).

There are several possible interpretations of our results. First, it might be risky to wait until the long-term mispricing is revealed. Exploiting such investment opportunities might be difficult and expensive, and it requires managers who are patient enough to resist the pressure of temporary losses. Such strategies accompanied with higher returns could be a driver of outperforming funds with high duration and high activity. Alternatively, the long-term character of the outperforming strategies supports also the active engagement channel and provide a possibility for shareholders to improve the performance of the over-weighted companies. Finally, our results could also be driven by very specific asset allocation strategies in particular markets, e.g., in emerging markets.

Our paper highlights the role activity and duration play in pension fund equity investment and shows some robust results. Our paper also contributes to the institutional herding literature by suggesting that pension funds which deviate from their peers (in combination with long holding duration) are able to outperform. This adds to Jiang and Verado (2018) who provide evidence that herding mutual funds under-perform their antiherding peers by more than 2% per year. Some open issues remain, however, related to behavior in other assets classes, the specific sample and the role of asset managers. Pension funds usually invest in several asset classes. While we provide evidence that pension funds that combine high *Active share*^{PF} with a long holding duration generate higher returns it is notable that our paper focuses on equity investment of pension funds only (cf. Bradley et al., 2016). It remains an open issue whether a similar relationship also holds, for example, for fixed income investments. In addition, although our results are based on a sample of Dutch pension funds (who are subject to country specific regulations), we expect them to hold in other pension market with similar characteristics. Nevertheless, it is important for future research to examine the activity-patience relationship in different institutional settings. Finally, we note the role of asset managers. In most cases, 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 directly implementing 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.

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 investments. They could mandate their asset managers to pursue buy-and-hold strategies for stocks selections that they think are attractive but which diverge from the consensus view. For supervisors, the challenge is to evaluate whether a pension fund that holds stocks that are at odds with received wisdom will also be able to hold these stocks for a considerable time. Our findings indicate that higher fund activity stems from both - the asset allocation channel and stock picking channel, but a quantitative comparison of the channels is beyond the scope of this paper. Future research should aim to look deeper into the decomposition of our findings due to strategic decisions (i.e., mandates) and stock picking. Defining the fraction of *Active share*^{PF} which is generated

through either channel can help sharpen the policy implications for all stakeholder involved.

Supplementary material

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.jbankfin.2020.105812.

CRediT authorship contribution statement

Tanja Artiga González: Conceptualization, Investigation, Writing - original draft. **Iman van Lelyveld:** Conceptualization, Writing - original draft. **Katarína Lučivjanská:** Conceptualization, Investigation, Writing - original draft.

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