Pension Fund Equity Performance: Herding Does Not Payoff

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ABSTRACT

Using a unique data set including the holding of pension funds in the Netherlands, I document that pension funds herd in individual securities. I introduce two pension-fund-level measures of herding. The first measure identifies the extent to which a pension fund acts as a leader. I show that leader pension funds do not outperform non-leader pension funds indicating that leaders and non-leaders have similar investment skills. The second measure identifies the extent to which a pension fund acts as a follower. I show that follower pension funds underperform non-follower pension funds by 1.32% on an annualized basis indicating that herding has a negative impact on performance. Herding is related to reputational concerns, as large corporate pension funds and industry-wide pension funds are more likely to be leaders.

Key words: herding, pension fund performance, asset allocation, investment skills

JEL classification: G11, G23.

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Public equity is one of the main asset classes within the portfolio of any pension fund. Internal or external asset managers are generally responsible to implement the investment policy within the asset class. This entails a number of decisions that affect the security selection. First, as pension funds invest globally, one important decision is the allocation across different geographical areas. Second, pension funds may decide to overweight some stock characteristics with respect to others and hence following some factors e.g., value vs growth or small vs large capitalization stocks. Pension funds may also decide to adopt sustainable investment strategies by excluding some industries or securities from their portfolios. Third, pension funds define benchmarks that identify their universe of eligible investments and give guidelines on performance assessment and asset manager compensation (Broeders and De Haan (2018)). The extent to which these benchmarks are closely tracked defines the passive or active nature of the investment mandate of an asset manager. These three decisions, as well as the security selection activity itself, can be affected by herding tendencies in the same way herding affects the pension funds' asset class mix (Broeders et al. (2016), Blake et al. (2017)).

Herding occurs when investors follow each other into and out of the same securities over time (Lakonishok et al. (1992)). Pension funds may herd because they infer information from each other's trades (Banerjee (1992)) or because they are concerned about relative underperformance with respect to their peer group (Scharfstein and Stein (1990)). Herding is a sequential behavior: it originates from an investor that trades a security. In the subsequent period, another investor trades, in the same direction, the same security by either observing or inferring the trade of the first investor. One unexplored feature of herding in the empirical literature is the identification of investors that move first and investors that follow. Less skilled or less informed investors may decide to herd on the trades of first movers (Jiang and Verardo (2018)). Therefore, it is important to clarify which criteria followers use to identify their leaders and whether followers can benefit from herding.

In this paper, I study herding in Dutch occupational pension funds' equity investments, and I investigate whether herding influences pension fund performance.[1] I show that pension funds herd as a group (Sias (2004)). Then, I introduce two pension-fund-level measures of herding.

[1] The literature on herding has mainly focused on mutual funds. A number of studies investigate the impact of herding on prices (Wermers (1999), Coval and Stafford (2007), Dasgupta et al. (2011a)). Others, similar to this study, relate herding to fund performance (Grinblatt et al. (1995), Wei et al. (2015).

The first measure identifies the extent to which a pension fund acts as a leader (non-leader). I define a leader (non-leader) as a pension fund whose trades today have a strong (poor) predictive power in explaining future trades of other pension funds. I show that leader pension funds do not outperform non-leader pension funds. Where performance is defined as the monthly return of each pension fund's equity portfolio. The second measure identifies the extent to which a pension fund acts as a follower (non-follower). I define a follower (non-follower) as a pension fund whose future trades are largely (poorly) explained by the aggregate trades of other pension funds today. I show that follower pension funds underperform non-follower pension funds by 1.32% on an annualized basis. I obtain similar results when I account for exposures to factors such as the global market risk premium, global size, global value, and global momentum. Therefore, underperformance is not driven by different risk exposures. In a multivariate predictive regression, herding negatively predicts future four-factor alphas after controlling for pension fund characteristics. Hence, herding negatively affect performance. This is likely due to the fact that by inferring information from others, pension funds acquire non-timely information. The leader pension funds do not appear to possess timely information, as they do not perform significantly better than both non-leaders and followers. Instead, non-followers appear to be the most skilled pension funds, as they outperform both followers and leaders.

The rich theoretical foundation for institutional herding divides herding into different categories[2]. The findings of this paper indicate that pension fund herding is linked to informational cascade and to reputational concerns. Models of informational cascades posit that investors herd by inferring information from each other (Bikhchandani et al. (1992) and Hirshleifer et al. (1994)). Some pension funds either fortuitously or owning better skills may acquire information first,[3] while others may infer information from the trades of better-informed pension funds and in turn herd. In line with informational cascades (Wermers (1999)), pension funds herding is stronger in markets with lower analyst coverage, and thus where inferring information can in principle be more valuable, such as small capitalization stocks and emerging markets. Moreover, small pension funds, which generally have less resources to invest in research, are more likely to be follower pension funds. Nevertheless,

[2]See Graham (1999), Nofsinger and Sias (1999) and Wermers (1999) for a detailed discussion of this classification.

[3]Pension funds owning better skills may decide to trade against the crowd i.e., anti-herd to exploit their advantage (Jiang and Verardo (2018)). Fund managers might also want to deviate from the crowd, because their bonus contract gives them an asymmetric incentive. In fact, asset management contracts establish compensation for gains, but no bonus penalty for losses.

follower pension funds underperform non-follower pension funds by 2.76% in emerging-markets.

If herding does not lead to greater performance, why do pension funds follow each other? The fear of underperforming the peer group and concerns about how others will assess their ability to make sound judgments can induce institutional investors to follow each other (Avery and Chevalier (1999), Bikhchandani and Sharma (2000)). In line with this reputational herding hypothesis, I show that industry-wide pension funds are more likely to be leader pension funds. Industry-wide pension funds are exposed to a high public attention and media coverage, as they deal with the interests of several social partners and employers. For example, some industry-wide pension funds publicly disclose their security holdings in their annual reports. This visibility can encourage conformity from other pension funds. In addition, large pension funds might be identified as more skilled ex ante (Andonov et al. (2012)). In line with this size argument, I show that large pension funds are more likely to be leaders in small capitalization stocks and emerging markets, where skills can indeed be valuable.[4] Moreover, pension funds that are categorized as leaders (non-leaders) in one month tend to be also categorized as leaders (non-leaders) in the subsequent months. Similarly, pension funds that are categorized as follower (non-follower) in one month tend to be also categorized as follower (non-follower) in the subsequent months. This indicates that herding might be a strategic decision, as it is related to permanent characteristics such as size and pension fund type.

I perform a number of tests to document that herding does not arise from reasons other than pension fund following each other into and out of the same securities. First, I show that herding does not arise because pension funds hold similar portfolios and reinvest net flows proportionally in the current portfolio weights. Therefore, pension funds do not mechanically follow each other into and out of the same securities over subsequent months because of corrleated flows. Second, I investigate if pension funds' preferences for securities with high (low) lag returns, large (small) market capitalization, or high (low) book-to-market can explain herding, in line with style-investing (Barberis and Shleifer (2003)). I find that lag returns, market capitalization, and book-to-market ratio account for little of the herding.

[4] Large pension funds also employ a large number of brokers that can spread order flows across all their clients (Barbon et al. (2019)). Brokers can therefore be a channel through which information about trades transfer across pension funds. Other channels through which information about trades can transfer across pension funds are: asset managers social ties and news. The concentration of the industry and the size of the country facilitate the creation of social ties and exchange of investment beliefs among asset managers (Cohen et al. (2008)). Asset manager may also infer information from the trades of other pension funds by reading news and financial reports.

Occupational pension funds are particularly suited to investigate herding because of a number of reasons that can foster this behavior. First, pension funds are subject to a similar solvency regulation, which can influence their demand for assets with specific characteristics (Greenwood and Vissing-Jorgensen (2018)).[5] Second, pension funds may respond with similar investment strategies to the long-term decline in market interest rates that affect the value of their liabilities (Domanski et al. (2017)). Third, pension funds are a homogeneous group of investors that might share preferences for securities with similar characteristics (Falkenstein (1996), Bennett et al. (2003)). For example, they might follow similar investment styles or favor securities of certain sectors or geographical areas. Fourth, reputational concerns are high among asset managers. Pension funds' investment performance is disclosed publicly, this performance faces the scrutiny of pension funds' stakeholders[6] and the board of trustees who can decide to replace the asset manager in case of poor performance. Fifth, the geographical proximity, the social network of pension fund administrators and common advisors facilitate the transfer of investment beliefs across pension funds (Bauer et al. (2018)).

The relation between herding and performance of pension funds is of pivotal importance due to the absence of market discipline. The investment performance of pension funds directly affects their funding ratio. In the Dutch context, the active participants in a poorly funded pension fund may face an increase in their contribution rate. Furthermore, active participants and retirees may experience a reduction in indexation or, if nothing else can be done to restore full funding, a reduction in accrued pension benefits.[7] Yet, it is rather difficult for participants to leave a pension fund in case of poor investment performance. They can only leave their pension fund by changing job and transferring accrued benefits from one pension funds to another. This "voting with their feet" would require finding a job at a corporation that has a better performing pension plan.

[5] In the European Union, 2016 IORP II directive established common standards ensuring the soundness of occupation pension funds. These general standards are then integrated by each member state's regulation. Several studies document the impact of regulation on the investment decisions of pension funds Andonov et al. (2017) in the US and Amir et al. (2010) in the UK. Moreover, Boon et al. (2018) show that the difference in regulation can explain the heterogeneity of asset allocations across pension funds in the Netherlands, US, and Canada.

[6] The performance of mandatory industry-wide pension funds is evaluated against a benchmark. If an industry wide pension fund underperforms this benchmark for five consecutive years the pension fund's stakeholders can contest the mandatory nature of the pension fund. For example, collective labor agreement in some industries establish that all companies within the industry must join the industry-wide pension fund set up by the industry organization. Individual companies can contest this mandatory nature and decide to leave if the industry pension fund consistently underperforms its benchmark for five consecutive years.

[7] Indexation is also known as a cost of living adjustment.

Therefore, plan beneficiaries bear part of the benefits and costs of herding. If pension fund asset managers infer timely information from others, and in turn herding leads to greater performance, then it can be beneficial to beneficiaries. However, if the information inferred are not timely, and in turn herding negatively influences pension fund performance, it will also negatively affect beneficiaries' welfare.[8]

With this study, I contribute to two strands of the literature. First, I contribute to the literature on pension fund performance. A number of studies link performance to pension funds' ability to access to cost efficiency (Bauer et al. (2010), Dyck and Pomorski (2011), Andonov et al. (2012) and Blake et al. (2013)). I concentrate on security selection by using a unique data set of the holding of pension funds. I examine if pension funds infer information from each other during the security-selection activity. Next, I relate herding to performance to gauge if the information inferred is correct and timely. I document that pension funds infer information from each other's trades. However, follower pension funds appear to infer information that are not timely, as herding negatively impacts their performance.

Second, I contribute to the empirical literature on herding. Previous papers measure herding at the security level as the correlation among institutional investors' demand for the same securities over time.[9] I introduce two pension-fund-level measures of herding that identify leaders and non-leaders, as well as followers and non-followers. These measures shed new light on the link between herding and pension fund characteristics and allow to identify the criteria that followers use to identify their leaders. Moreover, the findings of this paper complement earlier evidence of no herding among pension funds provided by Lakonishok et al. (1992). Over the past three decades, pension funds appear to have developed similarly diversified equity portfolios.

The remainder of the paper is organized as follows: Section I introduces the institutional setting and the data used for the study. Section II shows that pension funds herd as a group. Section III presents the measures for leader and follower pension funds. Section IV investigates the relation

[8]In other jurisdictions the benefit and costs of herding are borne by the sponsor (UK corporate pension funds) or by tax payers (US public pension funds).

[9]This literature has its origin in Lakonishok et al. (1992) who develops the first herding measure as the contemporaneous correlation of the demand of pension funds for the same security. Several other studies rely on this measure to investigate institutional herding (Grinblatt et al. (1995), Nofsinger and Sias (1999), Wermers (1999)). Sias (2004) measures herding as the correlation across institutional demand for a security over adjacent quarters. Dasgupta et al. (2011b) introduces another dynamic security-level measure of herding. These measures better capture the dynamic features of herding. I use Sias (2004) as a baseline model to show that Dutch pension funds herd as a group.

between herding and pension fund return, as well as the motivations underlying herding. Section V addresses alternative explanations for herding. Section VI concludes.

I. Data

A. The institutional setting

The Dutch pension system consists of three pillars. The first is a state pension that provides a basic income starting at the statutory age of retirement. The second pillar is a mandatory fully funded occupational pension. These pensions are administered by a pension fund or by an insurance company. The Dutch law distinguish three types of pension funds: industry-wide pension funds, corporate pension funds, and pension funds for independent professionals. The law keeps the sponsor and pension fund strictly separated. Pension funds are legally and financially independent from the companies. The third pillar consists of individual voluntary pensions.[10]

This study takes place in the occupational pension sector in which the dominant pension contract is a hybrid defined benefit (DB) - defined contribution (DC) scheme. The pension contract is a hybrid because it combines pre-defined benefits calculated on the average income history with solvency-contingent indexation of benefits and contributions (Ponds and Van Riel (2009)). This structure means that contributions can be raised, indexation stopped, and benefits partially cut in case of severe underfunding of the plan. The employer automatically enrolls its employees in the plan, and they cannot express individual preferences concerning contribution rate, which is defined by the law, or asset allocation, which is decided by pension fund's trustees and asset managers. Participants cannot leave the pension fund in which they are enrolled, unless they switch employers. The Dutch occupational pension funds manage a total of 1,323 billion euros corresponding to 170% of the Dutch GDP as of December 2018. Pension liabilities are discounted using the euro swap rates up to 30 years and the Ultimate Forward Rate (UFR) for longer maturities. The UFR is computed by the prudential supervisor of pension funds in the Netherlands, De Nederlandsche Bank (DNB).

[10]For a summary of the Dutch pension system see OECD (2017). For papers that describe the features and functioning of the Dutch pension regulation see e.g., Ponds and Van Riel (2009), Cui et al. (2011)

B. *Holding data*

The data for this study are the public equity holdings of Dutch institutional investors operating in the pension sector. The data are proprietary and provided by DNB. The sample consists of the public equity holdings of 44 pension funds and 18 pension asset management firms and corresponds to 98% of the value of all public equity investments in the Dutch pension fund industry. For a total of over 21,000 individual securities. The supervisor requires the asset managers of the largest 44 pension funds, the so-called system-relevant, to monthly report their holdings at the individual security level. Smaller pension funds are not required to directly report their holdings. However, DNB requires Dutch asset managers to report the security holdings of all their investment funds larger than 150 million euro. Asset managers must disclose the sector of origin and the shares held by each type of investor in their investment funds. For example, Achmea asset management reports that 40% of the assets of one of their equity funds is owned by pension funds, 40% by banks and 20% by insurance companies. I apply the following procedure to identify the securities managed on behalf of pension funds that are not required to directly report their holdings. First, I isolate all the investment funds mainly owned by pension funds; they hold more than 80% of the total assets of an investment fund every month. Second, I aggregate the holdings of all investment funds managed by the same asset manager. After this procedure, I am left with the security holdings of 18 asset management firms of pension funds that can be merged with the holdings reported by the asset management firms of the largest 44 pension funds. The result is a nearly complete picture of the equity investments of pension funds even though not all pension funds are required to report their security holdings. Throughout the paper I will use the term pension funds for simplicity, even though the security selection and consequently herding originates from the asset managers that are the actual decision makers.

Each holding is uniquely identified by its International Security Identification Number (ISIN). For each ISIN, the pension funds report the value in euros and the split-adjusted number of securities held at the beginning and end of each month as well as the value of the bought and sold securities throughout the month. The holding data are merged with security-level information such as stock price, total return, market capitalization, and book-to-market ratio from Factset. The sample includes international stocks. Since the data on holdings are in euros, the security-level information are converted to euros. The data set covers the period from January 2009 to December 2018 for a total of 120 months.

Table I reports the summary statistics of the holding data. The average equity portfolio of the institutions in the sample is 5.7 billion, and the median is 1.1 billion. During the sample period, pension funds are net buyers of equity, as the value of monthly purchases (227.3 million) is greater than the value of monthly sales (219.5 million). The average number of securities held is 1,464, and the median is 1,179. Pension funds report an average exposure to North American (US or Canada) securities of 32% (median 37%). European equity account for 43% of the portfolio, Asian and Pacific 12%, and emerging markets account for 13%.[11] Over the sample period, the average monthly gross portfolio return is 1.1%. See Appendix A for the calculation of pension fund returns. Pension funds report an average turnover ratio of 2% (median 0.6%) and an average flow of 0.04% (median -0.02%). Pension fund flows are driven by contributions coming in and benefits going out. Moreover, flows can capture the heterogeneity in pension funds' strategic asset allocations. For example, if a pension fund's board of trustees decide to increase the strategic allocation to fixed-income securities, this increase will translate into an outflow from the equity portfolio.[12]

II. Pension funds herding

In this section, I document that Dutch pension funds follow each other into and out of the same securities over time relying on the aggregate measure of herding introduced by Sias (2004).

A. Aggregate pension funds demand

Each month, I classify a pension fund as a buyer (seller) if the number of split-adjusted stocks held at the end of the month is greater (smaller) than the number of split-adjusted stocks held at the beginning. If the number of split-adjusted stocks is the same at the beginning and end of the month, the pension fund is classified as neither a buyer nor a seller. Also, a pension fund that buys and sells the same number of stocks within a month is classified as neither a buyer nor a seller. A pension fund is classified as a trader, if it is either a buyer or a seller. For each month, I calculate

[11] I classify developed countries as in Fama and French (2012), all the countries that are not classified as developed are then classified as emerging economies.

[12] Flows are computed following Sialm et al. (2015).

the raw fraction of pension funds buying security j during month t:

$$Raw\Delta_{j,t} = \frac{Nr.\ of\ Pension\ funds\ buying_{j,t}}{Nr.\ of\ Pension\ funds\ buying_{j,t} + Nr.\ of\ Pension\ funds\ selling_{j,t}} \tag{1}$$

I exclude the initiation and liquidation of each position. Namely, to be in the sample a pension fund must hold at least one stock at the beginning and at least one stock at the end of a month. Moreover, each security must have at least one pension fund trading the security during the month to be in the sample.

Table II presents the average number of securities with at least one, three, five, or ten trading funds over the 120 months in the sample, and the total number of securities traded in different time periods. The first column shows that on average there are 4,837 securities with at least one trading fund each month, 2,246 securities with at least three, 1,397 securities with at least five, and 428 securities with at least ten trading funds. These numbers are quite stable over time as shown by the next columns.

B. *Aggregate herding measure*

To measure herding, I first standardize the raw fraction of pension funds that buy (standardized pension fund demand):

$$\Delta_{j,t} = \frac{Raw\Delta_{j,t} - \overline{Raw\Delta_t}}{\sigma(Raw\Delta_{j,t})} \tag{2}$$

where $\overline{Raw\Delta_t}$ is the cross-sectional average (across J securities) raw fraction of pension funds that buy in month t, and $\sigma(Raw\Delta_{j,t})$ is the cross-sectional standard deviation (across J securities) of the raw fraction of pension funds that buy in month t. Second, for each month I estimate a cross-sectional (across J securities) regression of the standardized fraction of pension funds that buy security j in the current month, on the standardized fraction of pension funds that buy security j in the previous month. In other words, I regress the standardized demand for security j on the standardized lag demand for security j:

$$\Delta_{j,t} = \beta_t \Delta_{j,t-1} + \epsilon_{j,t}. \tag{3}$$

Because the data are standardized and there is only one independent variable, the coefficients of each cross-sectional regression in Equation (3) can be interpreted as the correlation between the standardized demand for security j ($\Delta_{j,t}$), and the standardized lag demand for security j ($\Delta_{j,t-1}$).[13] A positive correlation between the pension fund demand and the pension fund lag demand can occur because pension funds follow themselves into and out of the same security over subsequent months or because pension funds follow each other into and out of the same security over subsequent months; that is, they herd. Thus, the correlation between the demand this month and the demand last month can be decomposed into the portion that results from pension funds following themselves into and out of the same security over subsequent months and the portion that results from pension funds following each other into and out of the same security. Specifically, the fraction of funds that are buyers can be written as the sum of a series of dummy variables for each fund that equal one if the fund is a buyer and zero if it is a seller divided by the number of funds that are either buyers or sellers. As a result, the β coefficient in Equation (3) can be rewritten as:[14]

$$
\begin{aligned}
\beta_t &= \rho(\Delta_{j,t}, \Delta_{j,t-1}) \\
&= \left[\frac{1}{(J-1)\sigma(\Delta_{j,t})\sigma(\Delta_{j,t-1})}\right] \sum_{j=1}^{J} \left[\sum_{n=1}^{N_{j,t}} \frac{(d_{n,j,t} - \overline{Raw\Delta_t})(d_{n,j,t-1} - \overline{Raw\Delta_{t-1}})}{N_{j,t}N_{j,t-1}}\right] \\
&\quad + \left[\frac{1}{(J-1)\sigma(\Delta_{j,t})\sigma(\Delta_{j,t-1})}\right] \\
&\quad \times \sum_{j=1}^{J} \left[\sum_{n=1}^{N_{j,t}} \sum_{m=1, m\neq n}^{N_{j,t-1}} \frac{(d_{n,j,t} - \overline{Raw\Delta_t})(d_{m,j,t-1} - \overline{Raw\Delta_{t-1}})}{N_{j,t}N_{j,t-1}}\right]
\end{aligned} \tag{4}
$$

where $N_{j,t}$ is the number of pension funds trading security j in month t, and $d_{n,j,t}$ is a dummy variable that equals one (zero) if pension fund n buys (sells) security j in month t. $N_{j,t-1}$ is the number of pension funds trading security j in month $t-1$ and $d_{n,j,t-1}$ is a dummy variable that equals one (zero) if pension fund n buys (sells) security j in month $t-1$, and $d_{m,j,t-1}$ is a dummy variable that equals one (zero) if pension fund m ($m \neq n$) buys (sells) security j in month $t-1$.

The first term in the right-hand side of Equation (4) is the portion of the correlation that results

[13] The standardization of the data is necessary to interpret the coefficient in Equation (3) as a correlation. Then, I can split the correlation coefficient into two terms as described in Equation (4). Moreover, the standardization allows to aggregate the coefficients over time to directly compare them. Each regression coefficient depends on the scale of the data, if the pension funds' demand were not standardized, then the comparison of different cross-sectional regression coefficients would be inappropriate.

[14] For the proof see Sias (2004)

from pension funds following themselves into and out of the same securities over subsequent months. The second term in the right-hand side of Equation (4) is the portion of the correlation that results from pension funds following each other into and out of the same securities over subsequent months. The first term will be positive if pension fund n buys security j in month $t-1$ and t or sells security j in both months. The second term will be positive if pension fund n buys (sell) security j in month t and pension fund m buys (sell) security j in month $t-1$. The second term will be negative if pension fund n buys (sells) security j in month t and pension fund m sells (buys) security j in month $t-1$. In other words, pension funds exhibit anti-herding behavior. If the demand of pension fund n is not correlated with the lag demand of pension fund m, the second term will be zero, that is, pension funds do not herd.

Table III presents the time-series average coefficients from 119 cross-sectional regressions described in Equation (3) and the coefficient decomposition described in Equation (4). Panels A, B, and C show that pension funds follow themselves and each other into and out of the same securities. For securities with at least three trading funds, the correlation coefficient between the standardized fraction of pension funds that buy and the standardized lag fraction of pension funds that buy is 0.1973.[15] On average, 51% of the correlation, 0.1004/0.1973, results from pension funds herding. The remaining fraction of the correlation, 0.0969/0.1973, results from pension funds following themselves into and out of the same securities, i.e. spreading their trades over subsequent months. The results for the sample of securities with at least five and ten trading funds also show that pension funds herd and spread their trades over subsequent months.[16][17] The remained of the analysis will be carried out on the sample of securities with at least 3 traders. This choice is motivated by the fact that on the one hand, I am interested in documenting the determinants of herding and therefore a minimum number of traders in each security is necessary to study such a

[15] The standardization has little effect on the regression coefficient in Equation (3). Using the raw data instead of the standardized data, the slope coefficient is 0.1806 (t statistics = 30.32) when limiting the sample to securities with in more than three trading funds. The slope coefficient is 0.1830 (t statistics = 26.80) when limiting the sample to securities with more than five trading funds, and 0.1990 (t statistics = 20.10) when limiting the sample to securities with more than ten traders.

[16] In unreported results, I show that the fraction of the correlation that results from herding is 0.0503 for the sample that includes all securities traded. This finding is due to the fact that each month, there are a number of securities that are traded by only one pension fund for which the second component is by definition zero. This reduces the portion of correlation due to herding.

[17] In the Supplementary Tables, I show that the results are unchanged, if I estimate Equation (3) and Equation (4) excluding stocks of Dutch firms. Therefore herding is not driven by home bias or political pressure that might affect asset managers investment decisions (Bradley et al. (2016), Andonov et al. (2018)).

behavior. On the other hand, I am interested in linking herding to performance, therefore I want to have a realistic representation of the portfolios of the pension funds in the sample.

III. Leader and follower pension funds

Theoretical models of herding describe it as a dynamic behavior in which an agent infers information from the actions of others (Scharfstein and Stein (1990), Banerjee (1992)). Empirical studies measure herding among institutional investors as the correlation among investors' demands for the same security in the same period (Lakonishok et al. (1992)), or as the correlation of the aggregate institutional demand over adjacent periods (Sias (2004)). However, these measures do not completely capture the dynamics of the sequential decisions of institutional investors. Jiang and Verardo (2018) addresses this problem by developing a fund-level measure of institutional herding that captures the tendency of a fund manager to imitate the trading decisions of the institutional crowd. Yet, theoretical models posit that herding occurs after an agent through an action provides a first piece of information (either correct or wrong) to the crowd, which in turn follows. To better capture this sequential nature, and to understand the drivers of herding, I develop two fund-level measures that identify leaders and followers. The first measure identifies the pension funds that systematically provide the strongest signal to the crowd. I call these leader pension funds. A leader pension funds is defined as a pension fund whose trades today have a strong predictive power in explaining future trades of other pension funds.[18] In other words, a leader pension fund is a pension funds that is highly followed by others. The second measure identifies the extent to which a pension fund acts as a follower. I define a follower as a pension fund whose future trades are largely explained by the aggregate trades of other pension funds today. In other words, a follower pension fund is a pension fund with a high tendency to follow others.

A. Leader pension fund measure

To identify leader pension funds, I estimate the contribution of each pension fund's demand in explaining other pension funds' future demand. This is achieved with a three-step procedure.

[18]This definition is inspired by the concept of a bellwether firm, namely a firm whose fundamentals correlate most strongly with those of all other firms in the industry. Bellwether firms attract more analyst coverage; and when analysts revise a bellwether firm's earning forecast, it changes the prices of other firms significantly (Hameed et al. (2015)).

Specifically, I first run a cross-sectional (across J securities) regression of the demand for security j of pension fund n in month t on the lag demand of all other pension funds except pension fund m:

$$D_{n,j,t} = \alpha_{j,t} + \beta_1 D^m_{N,j,t-1} + \epsilon_{j,t} \tag{5}$$

where $D_{n,j,t}$ is the change in the number of split-adjusted shares of stock j in the portfolio of pension fund n during month t that is scaled by the number of split-adjusted shares held at the end of month $t-1$: $D_{n,j,t} = (num.Shares_{n,j,t} - num.Shares_{n,j,t-1})/num.Shares_{n,j,t-1}$. $D^m_{N,j,t-1}$ is the change in the number of split-adjusted shares of stock j in the portfolio of all pension funds other than m during month $t-1$:

$$D^m_{N,j,t-1} = \frac{(num.Shares_{N,j,t-1} - num.Shares_{m,j,t-1}) - (num.Shares_{N,j,t-2} - num.Shares_{m,j,t-2})}{(num.Shares_{N,j,t-2} - num.Shares_{m,j,t-2})} \tag{6}$$

where $num.Shares_{N,j,t-1}$ is the total number of split-adjusted shares of stock j in the portfolio of all pension funds in month $t-1$. Therefore, Equation (6) is the change in the aggregate ownership of pension funds, except m, of security j during month $t-1$.

Equation (5) is estimated each month for each pension fund n. The regression R^2 of Equation (5), $R^2_{n,excl.m}$, is the fraction of variation in pension fund n's demand at time t that is explained by the demand of all pension funds, excluding m, that trade in month $t-1$.

Second, I run the same regression but adding pension fund m's lag demand, $D_{m,j,t-1}$, which is the change in the number of split-adjusted shares of stock j in the portfolio of pension fund $m \neq n$ during month $t-1$: $D_{m,j,t-1} = (num.Shares_{m,j,t-1} - num.Shares_{m,j,t-2})/num.Shares_{m,j,t-2}$

$$D_{n,j,t} = \alpha_{j,t} + \beta_1 D^m_{N,j,t-1} + \beta_2 D_{m,j,t-1} + \epsilon_{j,t}. \tag{7}$$

Equation (7) is estimated each month for each pension fund n. The regression R^2 of Equation (7) is denoted $R^2_{n,incl.m}$. For each pair of pension funds (n,m) I compute $R^2_{n,incl.m}$ - $R^2_{n,excl.m}$; that is, the partial contribution of pension fund m's lag demand in explaining pension fund n's demand after controlling for the lag demand of all other pension funds.

Third, I compute an estimate of the average prediction power of each pension fund's demand by averaging $R^2_{n,incl.m}$ - $R^2_{n,excl.m}$ across the number of pension funds trading each month. For example, the average prediction power of pension fund m's demand is given by:

$$PW_{m,t} = \frac{1}{N_t - 1} \sum_{n=1 \; n \neq m}^{N_t} R^2_{n,incl.m} - R^2_{n,excl.m} \tag{8}$$

where N_t is the total number of pension funds that are classified as either a buyer or seller in month t. The higher $PW_{m,t}$, the better pension fund m's demand predicts the future demand of other pension funds. Each month, I define pension funds with the highest $PW_{m,t}$ as leader pension funds and pension funds with the lowest $PW_{m,t}$ as non-leader pension funds .

B. Follower pension fund measure

I rely on a similar method to develop the pension-fund-level measure of herding that identifies follower pension funds. I estimate the contribution of all other pension funds' demand in explaining each pension fund's future demand. Specifically, for each pension fund n, I run a cross-sectional (across J securities) regression of the demand for security j of pension fund n in month t on the lag demand of all other pension funds except pension fund n itself:

$$D_{n,j,t} = \alpha_{j,t} + \beta_1 D^n_{N,j,t-1} + \epsilon_{j,t} \tag{9}$$

where $D_{n,j,t}$ is defined as in the previous subsection and $D^n_{N,j,t-1}$ is defined in line with Equation (6) except for the fact that pension fund n is excluded from the aggregate demand in each regression. Next, I use the R^2 of Equation (9), run for pension fund n in month t, as the a measure of the degree of herding of pension fund n. The greater $R^2_{n,t}$, the more the aggregate demand of other pension funds explains the future demand of pension fund n; that is, the more pension fund n follows the demand of other pension funds.

IV. Herding and portfolio performance

In this section, I investigate the link between the measure for leader pension funds and investment skills, which are captured by gross portfolio returns. I also examine the link between follower pension funds and performance to investigate if follower pension funds can profit from herding.

I begin with an univariate portfolio test to link herding to portfolio returns. Then, I study the characteristics of leader and follower pension funds. Next, I estimate predictive regressions of pension fund performance that control for multiple pension fund characteristics

A. *Leader pension funds' portfolio performance*

Panel A of Table IV presents the summary statistics for the measure identifying leader pension funds: $PW_{m,t}$. These statistics are computed cross-sectionally each month and then averaged over 119 months. The results show that on average the additional prediction power of each pension fund's lag demand in explaining other pension funds' demand is 19.35% with a standard deviation of 8.86%. Most importantly, these results show that the measure of the prediction power of demand has substantial heterogeneity, varying from 6.22% (5th percentile) to 35.31% (95th percentile).[19] It is precisely this cross-sectional heterogeneity that is the focus of the analysis on leaders' performance.

I use a portfolio-based analysis to examine the difference in performance between leader pension funds and non-leader pension funds. At the end of each month, I sort pension funds into five portfolios based on the measure $PW_{m,t}$. Next, I compute equally weighted returns for each quintile portfolio over the next month and quarter. Then, I estimate the risk-adjusted returns of these portfolios as intercepts from time-series regressions on the capital asset pricing model (CAPM)[20] and the global three-factor model of Fama and French (2012) augmented with the global momentum factor.[21] To account for the fact that pension funds hold a sizable portion of their equity portfolio in North American stocks, and that the US stock market has outperformed global indices during the sample period, I also estimate the risk-adjusted returns on the North American market risk premium, size and value factors. As the risk-free rate, I use the U.S. one month T-bill rate in all specifications. If leader pension funds possess better investment skills or more timely information than non leaders, this will translate into a higher portfolio returns.

[19] It can be that in some month a pension fund m does not trade any of the securities that are traded in the next month by other pension funds. In this case $PW_{m,t}$ is set to zero and excluded from the analysis because the demand of pension fund m cannot predict the future demand of other pension funds. Excluding these values has little effect on the results as only 188 observations are excluded. In fact, if zero $PW_{m,t}$ are included then the average prediction power of each pension fund's demand in explaining other pension funds' demand is 18.71% with a standard deviation of 9.37%. Moreover, the 5th percentile is 3.87% and the 95th percentile is 35.11%.

[20] Since the data set includes international security holdings, to compute the CAPM alphas I use the monthly total returns on the MSCI All Country World Index (ACWI) as the market return.

[21] The global market return, size, value, and momentum factors, as well as the North American risk factors, are retrieved from Kenneth French's website: `https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/`

Panel B of Table IV presents the returns of the pension fund quintile portfolios. The top row reports the average value of the $PW_{m,t}$ measure for each quintile portfolio in month t. Pension funds in the top quintile are leaders (column 5). Pension funds in the bottom quintile (column 1) are non-leaders. Panel B shows that, leader pension funds do not outperform non-leader pension funds in the month and in the quarter after portfolio formation. In fact, the difference between columns (5) and (1) is not significantly different from zero considering both the average raw returns and the risk-adjusted returns. Each quintile portfolio reports an average monthly return of about 1%. After correcting for the risk loading on the MSCI ACWI, the results show that pension fund returns are due to market exposure. Similarly, pension funds exhibit no alpha above and beyond the global four-factor model or North American three-factor model.

Looking at the cumulative three-months returns, leader pension funds also do not outperform non-leader pension funds. In fact, the difference between the average and risk-adjusted returns of the top and bottom quintile portfolios is not statistically different from zero. The quintile portfolio of leader pension funds has a cumulative return of 3.48% and a cumulative alpha over the MSCI ACWI of 0.33%, but no alpha after using the global four-factor model or North American three-factor model. The quintile portfolio of non-leader pension funds report a cumulative return of 3.58% and a cumulative alpha over the MSCI ACWI of 0.43%, but no alpha after using the global four-factor model or North American three-factor model.

In sum, cross-sectional differences in pension funds $PW_{m,t}$ do not predict a difference in the performances of pension funds. The differentials in the risk-adjusted returns also show no difference. These findings indicate that leader pension funds do not possess better investment skills than non-leader pension funds.[22]

In Appendix B, I investigate the relation between $PW_{m,t}$ and the portfolio returns in subsets of the market in which herding can be more valuable due to high information asymmetry. In markets less covered by analysts the incentive and potential benefits of herding can be higher for less skilled or poorly informed pension funds (Wermers (1999)). I replicate the quintile portfolio analysis focusing on small capitalization stocks opposed to large capitalization stocks, and emerging market stocks opposed to developed market stocks. Small-capitalization securities are less covered

[22]The results are robust to alternative criteria in the portfolio formation. In the Supplementary Tables, I replicate the analysis forming portfolios based on terciles of $PW_{m,t}$ and the results are unchanged.

by analyst forecasts, for this reason institutional investors may infer information from the trades of others and value less their own noisy private information. If leader pension funds have better skills that allow to capture timely information, likely they would use this advantaged position in markets where information asymmetry is greater. Hence, leader pension funds will outperform other pension funds. A similar hypothesis can be generalized for emerging market securities (Dyck et al. (2013)). The results in Table XII and Table XIII show that leader pension funds do not perform significantly better than non-leader pension funds also in small capitalization stocks and emerging markets. This provides additional evidence that leader pension funds and non-leader pension funds appear to have rather similar investment skills.

B. Follower pension funds portfolio performance

If leader pension funds are not more skilled than non-leader pension funds, can follower pension funds profit from herding? To address this question, I identify the pension funds that herd the most i.e., the followers, and I compare their performance with the performance of pension funds that herd the least i.e., non-followers. Panel A of Table V presents the summary statistics of the second herding measure: R_n^2. The mean of R_n^2 is 4% that indicates that on average the lag demand of all other pension funds explains 4% of the variation in each pension fund's demand. In panel B, I use a portfolio-based analysis to examine the difference in performance between follower pension funds and non-follower pension funds. At the end of each month, I sort pension funds into five portfolios based on the measure R_n^2. Next, I compute equally weighted returns for each quintile portfolio over the next month and quarter. Then, I estimate the risk-adjusted returns of these portfolios as intercepts from time series regressions that use the same risk factors presented in the previous subsection.

Panel B of Table V presents the returns of the quintile portfolios. In the top row, I summarize the average R_n^2 in each quintile. Pension funds in the top quintile are follower pension funds (column 5). Non-follower pension funds are included in the bottom quintile portfolio (column 1). The results show that in the month following portfolio formation, the pension funds with the highest herding tendency underperform the pension funds with the lowest herding tendency by 0.11% per month. This means a return differential of 1.32% per year. The performance difference between follower and non-follower pension funds cannot be attributed to differences in factor risk exposure, as the differences in alphas from the CAPM, Global 4-factor model and North American 3-factor model are: -0.12%, -0.10%, and -0.10%, and statistically significant. Three months after portfolio formation the quintile portfolio of follower pension funds underperform the quintile portfolio of non-follower pension funds by 0.22%. However, the difference disappears after correcting for risk factors. This suggests that over a quarter pension funds that herd more are exposed to the same risk factors as pension funds that herd less.

In Appendix B, I replicate the quintile portfolio analysis in markets with high information asymmetries. I compute quintile portfolios based on R_n^2 in small capitalization stocks opposed to large capitalization stocks, and in emerging market stocks opposed to developed market stocks. Table XIV shows that pension funds herd more in small capitalization stocks than large capitalization stocks, as the average R_n^2 in each quintile is larger when limiting the sample to small stocks (Panel A) than when limiting the sample to large stocks (Panel B). However, follower pension funds do not perform differently than non-follower pension funds in both small and large-capitalization stocks. On the other hand, Table XV shows that pension funds herd more in emerging markets than in developed markets, as the average R_n^2 in each quintile is larger in the sample of emerging-market stocks (Panel B) than in the sample of developed-country stocks (Panel A). Moreover, follower pension funds underperform non-follower pension funds by 0.12% in developed markets and by 0.23% in emerging markets that corresponds to 2.76% on an annualized basis.

These results combined indicate that herding has a negative impact on performance, as pension funds that herd more underperform pension funds that herd less. This is likely due to the fact that by inferring information from others, pension funds might acquire non-timely information. In fact, the leader pension funds do not appear to possess timely information, as they do not perform significantly better than non-leader pension funds. In Table VI, I also show that leaders have no significantly different returns from followers. However, leader underperform non-followers by 0.09%, and leaders also undedrpeform non-followers by 0.07% on a monthly basis. These results indicate that the better-skilled pension exhibit anti-herding behavior in line with the evidence from mutual funds (Jiang and Verardo (2018)).

Moreover, the measures $PW_{m,t}$ and R_n^2 are relatively stable over time. Pension funds that are categorized as leaders (non-leaders) in one month tend to be also categorized as leaders (non-leaders) in the subsequent months. Similarly, pension funds that are categorized as follower (non-follower) in one month tend to be also categorized as follower (non-follower) in the subsequent months. In Appendix C, I show that pension fund that are more often categorized as leaders do not perform better than pension funds that are more often categorized as non-leaders. Pension funds that are more often categorized as followers underperform pension funds that are more often categorized as non-followers by 2.04% per year. This indicates that herding might be a strategic decision and it might be related to pension fund characteristics.

C. Determinants of leadership among pension funds

The results from the previous subsections lead to a natural question: if herding does not lead to greater performance, why do pension funds follow each other? In this subsection, I investigate the relation between PW_m and several pension fund characteristics to understand which are the characteristics of leader pension funds that might drive other pension funds to follow them. Similarly, I investigate the relation between R_n^2 and the same pension fund characteristics to understand what might drive pension funds to herd.

To address this question, I begin by estimating panel regressions of PW_m on a group of fund characteristics including: the type of institution, that is; a categorical variable to identify either industry-wide pension funds, corporate pension funds, or pension asset management firms.[23] Other characteristics are pension funds size (measured as the natural logarithm of the total equity portfolio), turnover, flow, and past returns. Given that leaders might not be the same across different markets, I investigate the relation between PW_m and pension fund characteristics in developed and emerging markets separately as well as in large and small capitalization stocks separately. Columns (1), (3), (5), and (7) in Table VII present the results for each subset of securities. As a robustness test, I also estimate logit regressions in which the dependent variable equals one when a pension fund is classified as leader pension fund i.e., it belongs to the 5^{th} quintile of PW, in a given moth. The logit regressions are presented in columns (2), (4), (6), and (8).

The results in columns (1) and (2) show that the coefficient associated to industry-wide pension funds is positive and significant in both specifications. This finding indicates that industry-wide pension funds have greater PW_m and are significantly more likely to be leader pension funds than

[23]Pension asset management firms are asset management firms that report the holdings of pension funds that are not required to directly report. Therefore, these firms manage asset of relatively small pension funds.

pension asset management firms (the omitted category) in developed markets. Similar results (and with coefficients of similar magnitude) are found in columns (5) and (6) for large capitalization stocks. The results in columns (3) and (4) show that large and corporate pension funds display greater PW_m and are significantly more likely to be leader pension funds than pension asset management firms in emerging markets. Moreover, the results in columns (6) and (7) show that large pension funds display greater PW_m and are significantly more likely to be categorized as leader pension funds in small capitalization stocks.

Next, I estimate panel regressions of R_n^2 on pension fund characteristics to investigate factors that might drive herding. As a robustness test, I also estimate logit regressions in which the dependent variable is a binary variable that equals one if a pension fund is classified as follower, that is; it belongs to the 5^{th} quintile of the R_n^2 distribution in a given month. Table VIII presents the results and shows that in all equity markets, small pension funds display a higher R_n^2 and are more likely to be followers. Moreover, pension funds with a lower turnover ratio are also associated with a higher R_n^2 and therefore are more likely to be followers. Thus, the pension funds that herd more are generally small and trade less frequently.

These results have two non-mutually exclusive interpretations. First, the fact that large (small) pension funds are more likely to be leader (follower) pension funds in markets with high information asymmetries indicates that pension funds engage in herding from informational cascade. Large pension funds might be identified as better informed and more skilled ex ante by smaller pension funds that in turn infer information from these larger pension funds' trades. Second, the fact that industry-wide pension funds are more likely to be leader pension funds in developed markets and large capitalization stocks i.e., the largest share of each fund's equity portfolio, indicates that pension funds herd because of reputational concerns as well. Industry-wide pension funds interact with a substantial number of social partners, as they are associated with multiple employers. These features translate into larger media coverage and public attention (Goyal and Wahal (2008)). Therefore, other pension funds might decide to follow industry-wide pension funds to enhance the market perception of their ability or because of concern about how others will assess their skills in the event of poor performance (Scharfstein and Stein (1990)). Information about industry-wide pension funds' investment strategies may also be more easily observable by others. For example, some industry-wide pension funds publicly disclose their security holdings in their annual reports.

Moreover, industry-wide pension funds may employ several brokers who can spread their order flows across their other clients (Barbon et al. (2019)).

D. *Return prediction*

To further explore the relation between returns and pension fund herding, I estimate multivariate regressions on the performance of pension funds. The measure of performance that I use is the monthly global four-factor alpha estimated from the the realized gross return of each pension fund in excess of the U.S. one month T-bill rate. The factor loadings are estimated with a rolling window time-series regression of the pension fund returns over the previous three years.

Table IX presents the predictive panel regression results. Columns (1) and (3) show the univariate regressions of the four-factor gross alphas on the lag measure of leader pension funds (PW_m) and on a dummy that equals one when the pension fund is categorized as a leader pension fund and zero otherwise. Columns (2) and (4) control for pension fund characteristics. I find that the lag PW_m measure does not predict performance, which is in line with the quintile-portfolio analysis. In column (1), the slope coefficient associated to the past level of PW_m is negative and significant at the 10% level, although economically very small. In fact, a 1% increase in the past level of PW_m is associated with a 0.0016 percentage points lower monthly alpha of a pension fund. After controlling for pension fund characteristics, the relation between performance and the past PW_m measure disappears.

Columns (5) and (7) show the results of the univariate regressions of the four-factor gross alphas on the lag herding measure (R_n^2) and on a dummy that equals one when the pension fund is categorized as a follower and zero otherwise. Columns (2) and (4) control for the influence of pension fund characteristics. The results show that the herding measure negatively predicts future performance, which is in line with the quintile-portfolio analysis. The slope coefficient associated with the past level of R_n^2 is negative and significant at the 1% level. A 1% increase in the past level of R_n^2 is associated with a 0.0023 percentage points lower monthly alpha of a pension fund. After controlling for pension fund characteristics, the relation between performance and herding remains significantly negative and almost unchanged in magnitude (β=-0.0020). Columns (7) and (8) indicate that being classified as follower in a month predicts a 0.005 percentage points lower monthly alpha in the next month.

Table IX also indicates that corporate pension funds exhibit greater performance than pension asset management firms, and that low portfolio turnover positively predicts future alpha, which is in line with the results in the studies on mutual funds (Carhart (1997)). Moreover, size does not predict better future performance in public equity. This finding is in line with Bauer et al. (2010) who show that large pension funds might be unable to respond quickly to news or might decide to allocate part of their equity portfolio to illiquid stocks.

In sum, the cross-sectional differences in PW_m do not predict differences in pension fund performance. Pension funds that are most followed in one month are not associated with greater performance in the subsequent month after controlling for pension fund characteristics. Conversely, R_n^2 is associated with lower future performance. In line with the quintile-portfolio analysis, herding negatively impact performance.

V. Alternative explanations for herding

The correlation between the fraction of pension funds that buy this month and the fraction of pension funds that buy last month might arise mechanically for reasons other than pension funds following themselves or each other into and out the same securities over subsequent months. For example, pension funds might display correlated trades because they hold similar portfolios and have correlated net flows, or because of style investing (Barberis and Shleifer (2003)).

A. *Habit investing*

Pension funds might display correlated trades because they hold similar portfolios. In this case, cross-sectional and time-series correlations in their net flows could result in correlated trades. First, if pension funds have similar portfolios i.e., they hold many of the same securities; second, if pension funds' inflows (outflows) display positive cross-sectional and time-series correlation i.e., participants contributions (benefits) are paid in the same period and are exposed to common shocks; third, if pension funds invest their contributions proportionally into existing portfolios, then pension funds will mechanically follow each other into the same securities over subsequent periods. This type of herding is defined as "habit investing".[24] To investigate if habit investing drives herding, I

[24] Habit investing can also occur if pension funds follow passive strategies that track the same index. In this case, contributions will be reinvested (divested) proportionally in all securities to mimic the weights of each security in the

examine the correlation between the fraction of pension funds that increase the return-adjusted portfolio weights over subsequent months, in line with Sias (2004). If pension funds' objective is to maintain similar portfolios over time, when new contributions are flowing in, pension funds would buy securities in proportion to their current holdings. Therefore, portfolio weights would not change. Alternatively, if pension funds follow themselves and each other into the same security for reasons other than maintaining constant portfolio weights and correlated net-flows, then the fraction of pension funds that increase their portfolio weights will be positively correlated over subsequent months.

To test this hypothesis, I begin by defining the return-adjusted portfolio weight in each security as the month-end portfolio weight if no trades were made throughout the month. For each security and month between January 2009 and December 2018, I define $V_{n,j,t}$ as the value of pension fund n's position in security j at the end of month t i.e., the price at the end of month t times the number of split-adjusted securities held. Pension fund n is defined as increasing its return-adjusted portfolio weight (buyer) if its month-end portfolio weight ($w^{adj}_{n,j,t}$) is greater than its return-adjusted beginning of month portfolio weight ($w^{adj}_{n,j,t-1}$)

$$w^{adj}_{n,j,t} > w^{adj}_{n,j,t-1} \equiv \frac{V_{n,j,t}}{\sum_{j=1}^{J} V_{n,j,t}} > \frac{V_{n,j,t-1}(1+r_{j,t})}{\sum_{j=1}^{J} V_{n,j,t-1}(1+r_{j,t})} \tag{10}$$

where $r_{j,t}$ is the return of security j in month t.[25] Pension fund n is defined as decreasing its return-adjusted portfolio weight (seller) if its month-end portfolio weight ($w^{adj}_{n,j,t}$) is smaller than its return-adjusted beginning-of-month portfolio weight ($w^{adj}_{n,j,t-1}$). If $w^{adj}_{n,j,t}$ equals $w^{adj}_{n,j,t-1}$, pension fund n is classified as neither a buyer nor a seller.

Next, for each security and month between January 2009 and December 2018, I compute the raw fraction of pension funds that increase their return-adjusted portfolio weights for the security:

index. Even if pension funds track passively the same index, herding might still be costly for late followers. In fact, pension funds that are the last ones to rebalance their portfolio in line with the underlying index may face negative price impacts as earlier trades have influenced the current prices

[25]Since pension funds invest in international securities $r_{j,t}$ is not only the total stock return, but it also includes appreciation and depreciation due to exchange rate fluctuations.

$$Raw\Delta^{w}_{j,t} = \frac{Nr.\ of\ Pension\ funds\ increasing\ w^{adj}_{n,j,t}}{Nr.\ of\ Pension\ funds\ increasing\ w^{adj}_{n,j,t} + Nr.\ of\ Pension\ funds\ decreasing\ w^{adj}_{n,j,t}} \quad (11)$$

Each month, I standardize $Raw\Delta^{w}_{j,t}$ to have a mean equal zero and a variance equal one, as in Equation (2). Then, I estimate a cross-sectional regression (across J securities) of the standardized fraction of pension funds increasing their return-adjusted portfolio weight on the standardized lag fraction of pension funds increasing their return-adjusted portfolio weights for each month, as in Equation (3). Next, I decompose the regression coefficient into the portion of correlations due to pension funds following themselves and each other into and out of the same securities, as in Equation (4). Table X presents the time-series average of the 119 correlation coefficients and the time-series average of the two components of the correlation. The results show that the faction of pension funds that increase their return-adjusted portfolio weights is correlated with the lag fraction of pension funds that increase their return-adjusted portfolio weights. Both the portion of correlations that arise from pension funds following their own return-adjusted portfolio weight changes and each other's return-adjusted portfolio weight changes are statistically and significantly different from zero, although smaller in magnitude than coefficients in Table III. Therefore, herding is not completely driven by pension funds mechanically reinvesting their net flows in the same portion as the existing holdings, that is, habit investing.

B. Herding and style investing

Pension funds might herd because of common investment styles. If pension funds pursue style investing, they will invest in securities with particular characteristics like large capitalization stocks, high book-to-market ratios, or momentum. For example, pension funds might herd because their demand is positively correlated with the prior month security returns, if pension funds are momentum traders.[26] To test this conjecture, I add the lag standardized return of the security in Equation (3). Specifically, for each month I regress the standardized fraction of pension funds

[26]Momentum trading is a form of characteristics herding, that is, pension funds might follow each other because they are attracted by securities with high lag returns. Several studies document that institutional investors are momentum traders (see, e.g., Grinblatt et al. (1995), Nofsinger and Sias (1999), Wermers (1999), Sias (2004), Sias et al. (2006), Sias et al. (2015)).

that buy security j on the lag standardized fraction of pension funds that buy security j and the standardized lag return of j:

$$\Delta_{j,t} = \beta_{1,t}\Delta_{j,t-1} + \beta_{2,t}r_{j,t-1} + \epsilon_{j,t} \tag{12}$$

All the variables are standardized in such a way to have a mean equal to zero and a variance equal to one each month. To account for other styles, I also estimate Equation (12) by replacing the lag standardized return with the lag standardized market capitalization and the lag standardized book-to-market ratio. Moreover, I estimate Equation (12) by adding all three security characteristics. Table XI presents the time-series average of the regression coefficients for the samples that include all securities with at least three, five, or ten traders.

The results show that adding the lag standardized return, or other lag standardized stock characteristics, to the regression has little impact on herding. In all samples, the average coefficients associated with the lag standardized fraction of pension funds that buy are comparable in magnitude to the average coefficients in TableIII. The average coefficient associated with the lag standardized return, or other stock characteristics are small compared to the average coefficients associated with the lag standardized fraction of pension funds that buy. Furthermore, the average R^2 in all panels of Table XI are similar to the average R^2 in TableIII. Therefore, adding lag returns, or other stock characteristics, does not significantly improve the model.

The average coefficient associated with the lag standardized return is not statistically different from zero when limiting the sample to securities with at least three traders. In the sample of securities with at least five or ten traders the average coefficient associated with the lag standardized return is negative, that means the pension funds are counter-cyclical traders rather than momentum traders. To conclude, herding of pension funds is not driven by past returns, security size, or book-to-market ratio. Even if all the three styles are added together in the regression, the results remain unchanged.

VI. Conclusion

In this paper, I study herding in Dutch occupational pension funds' equity investments, and I investigate whether herding influences pension fund performance. I begin my analysis by measuring herding across all pension funds in line with Sias (2004). Then, I develop two pension-fund-level measures of herding. The first measure identifies the extent to which a pension fund acts as a leader (non-leader). I define a leader (non-leader) as a pension fund whose trades today have a strong (poor) predictive power in explaining future trades of other pension funds. The second measure identifies the extent to which a pension fund acts as a follower (non-follower). I define a follower (non-follower) as a pension fund whose future trades are largely (poorly) explained by the aggregate trades of other pension funds today.

I find that pension funds follow each other into and out of the same securities over subsequent months. However, leader pension funds do not perform better than non-leader pension funds indicating that leaders are not better skilled than non-leaders. Follower pension funds underperform non-follower pension funds by 1.32% on an annualized basis and this result is not driven by different risk exposures. Therefore, herding negatively impacts performance, as follower pension funds seem unable to acquire timely information from leaders.

If herding is not associated with greater performance, why do pension funds decide to herd? My findings are consistent with two explanation. First, pension funds herd because of reputational concerns, as industry-wide pension funds are more likely to be leader pension funds. Due to the large number of social partners and external advisors involved in industry-wide pension funds, information about the leaders' investment strategies might be more accessible to others. Therefore, other pension funds may desire to conform to these leaders because they are concerned about the external perception of their investment ability. Second, pension funds herd because they try to infer information form each other. Small pension funds are more likely to be categorized as follower pension funds, and large pension funds are more likely to be leaders in small capitalization stocks or emerging markets, where inferring information can in principle be more valuable because of information asymmetry. Aggregate pension funds herding is also more pronounced in these markets. Therefore, small pension funds might infer information from large pension funds based on the ex-ante and not accurate judgment of their investment skills.

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Table I: **Summary statistics**
The table presents the time-series and cross-sectional mean, median, standard deviation, 5^{th}, 25^{th}, 75^{th} and 95^{th} percentile of the portfolio characteristics of pension funds. Portfolio characteristics are the total purchases and sells during each month in thousands of euros; the total equity portfolio at end of each month in thousands of euros; the number of individual securities (ISINs) purchased or sold during the month; the total number of individual securities (ISINs) held at the beginning of each month; the share of the equity portfolio invested in each geographical area; the monthly portfolio return (value weighted); the turnover ratio and flows.

	Obs.	Mean	Std. Dev.	p5	p25	p50	p75	p95
Purchases	5,736	227,589	985,155	123.00	5,098	20,169	85,376	654049
Sells	5,736	219,932	956,622	0.00	3,854	18,086	78,498	692,453
Tot. portfolio	5,736	5,772,178	20,012,368	101,796	466,856	1,143,676	3,204,825	16,447,118
Nr. ISIN bought	5,736	237.79	366.26	2.00	30.00	89.00	279.00	1,042.00
Nr. ISIN sold	5,736	209.57	375.63	0.00	18.00	65.00	214.50	1,003.00
Nr. ISIN held	5,736	1,464.15	1,371.94	102.00	340.00	1,178.00	2,053.00	4,162.00
Share Europe	5,736	0.4318	0.2395	0.1125	0.2706	0.3744	0.5290	0.9589
Share North America	5,736	0.3209	0.1770	0.0000	0.2222	0.3674	0.4453	0.5762
Share Asia & Pacific	5,736	0.1166	0.1372	0.0000	0.0494	0.1082	0.1433	0.2358
Share developed	5,736	0.8693	0.1604	0.6148	0.8026	0.9349	0.9777	0.9925
Share emerging	5,736	0.1294	0.1603	0.0066	0.0215	0.0627	0.1958	0.3841
Monthly return	5,736	0.0111	0.0328	-0.0454	-0.0069	0.0113	0.0315	0.0675
Turnover	5,736	0.0228	0.1346	0.0002	0.0020	0.0059	0.0175	0.0806
Flow	5,736	0.0004	0.1442	-0.0545	-0.0077	-0.0015	0.0051	0.0444

Table II: **Number of securities traded by pension funds over time**
For each security and month between January 2009 and December 2018, I compute the number of pension funds that trade the security. Pension funds are defined as traders if they are either buyers or sellers that depend on if they hold either a greater or smaller number of split-adjusted securities at the end of the month than they held at the beginning. If a pension fund holds the same number of split-adjusted securities at at the end of the month as it held at the beginning, it is not classified as a trader. Also, a pension fund is not classified as a trader, if it buys and sells the same number of split-adjusted securities during the month. The first column of Panel A presents the time-series average of the number of securities with at least 1, 3, 5 or 10 pension funds trading over the 120 months in the sample. The next columns show the number of securities with at least 1, 3, 5 or 10 pension funds trading them in January 2009, June 2011, December 2013, June 2016, and December 2018.

	Avg. all periods	Jan. 2009	Jun. 2011	Dec. 2013	Jun. 2016	Dec. 2018
Panel A: Nr. of securities with						
$\geq$ 1 pension fund trading	4,837	4,611	4,579	4,352	5,126	4,742
$\geq$ 3 pension funds trading	2,246	1,970	2,017	1,838	2,502	2,159
$\geq$ 5 pension funds trading	1,397	1,136	1,216	962	1,637	1,372
$\geq$ 10 pension funds trading	428	362	366	205	592	483

Table III: **Aggregate herding measure**
For each security and month between January 2009 and December 2018, I compute the fraction of pension funds (Pf) that increase their position in the security, as in Equation (1). Pension funds are defined as increasing their position (buyers) if they hold a greater number of split-adjusted securities at the end of the month than they held at the beginning. I standardize both the fraction of pension funds that buy and the lag fraction of pension funds that buy to have a zero mean and a unit variance. I estimate 119 monthly cross-sectional regression of the fraction of pension funds that buy on the lag fraction of pension funds that buy, as in Equation (3). Because there is a single independent variable in each regression and all data are standardized, the regression coefficients can be interpreted as a correlation. The first column presents the time-series average of 119 correlation coefficients and the associated t-statistic in parentheses. The t-statistics are computed from the time-series standard errors. The second and third column give the portion of the correlations that results from pension funds following their own traders and the portion of the correlations that results from pension funds following other pension funds' trades, that is, herding as described in Equation (4). The fourth column report the time-series average of the R^2 of the 119 cross-sectional regressions. Panels A, B, and C show the average coefficients when limiting the sample to securities with at least 3, 5 or 10 traders. The * indicates statistical significance at 10% level, ** at % 5 percent and *** at 1% level.

	Time-series avg. β coeff.	Pf. following their own trades	Pf. following others' trades	Avg. R^2
Panel A: Securities with	0.1973***	0.0969***	0.1004***	0.0431***
$\geq$ 3 pension funds trading	(33.38)	(33.57)	(18.18)	(18.87)
Panel B: Securities with	0.1949***	0.0818***	0.1131***	0.0431***
$\geq$ 5 pension funds trading	(29.44)	(26.24)	(16.82)	(16.79)
Panel C: Securities with	0.1996***	0.0674***	0.1322***	0.0499***
$\geq$ 10 pension funds trading	(21.55)	(16.96)	(14.04)	(12.34)

Table IV: Leader pension funds and portfolio performance

In Panel A, I present the summary statistics of $PW_{m,t}$: the indicator of the power of a pension fund's demand in predicting the future demand of other pension funds. $PW_{m,t}$ is estimated following the steps outlined in Section III and captures the extent to which pension funds are followed by others. Pension funds with high $PW_{m,t}$ are defined as leader pension funds. Panel B presents the performance of quintile portfolios of pension funds that are formed on the basis of this measure for leader pension funds. The quintile portfolios are formed at the end of each month from February 2009 to December 2018 and held for one or three months. I report equally weighted returns for each quintile portfolio over the next month and quarter (cumulative three-month returns). Quintile 5 is the portfolio of leader pension funds. Quintile 1 is the portfolio of non-leaders. I also compute the risk-adjusted returns based on the CAPM and the Fama and French (2012) global size, value, and momentum factors as well as North-American size and value factors. The risk-adjusted returns are the intercept from a time-series regression of the quintile portfolios excess returns over the U.S. one month T-bill rate on the risk factors. The CAPM market return is given by the monthly total return on the MSCI All Country World Index. For the time-series regression on North-American factors the market risk premium is the return on the region's value-weighted market portfolio minus the U.S. one month T-bill rate. All factors are converted into euro returns. The t-statistics are in parentheses and are computed using Newey-West standard errors with three lags. The * indicates statistical significance at the 10% level, ** at the % 5 percent, and *** at the1% level.

	Panel A: Summary statistics of the leader pension funds measure					
	mean	sd	p5	p25	p75	p95
$PW_{m,t}$	0.1935	0.0886	0.0622	0.1289	0.2495	0.3531
	Panel B: Leader pension funds and portfolio performance					
Quintile	(1)	(2)	(3)	(4)	(5)	5-1
Avg. PW_t	0.0877	0.1454	0.1887	0.2375	0.3183	0.2306
			Return month t+1 (%)			
Average	1.1016***	1.1979***	1.1704***	1.0458***	1.0841***	-0.0175
	(3.82)	(4.10)	(4.04)	(3.62)	(3.84)	(-0.41)
CAPM α_{MSCI}	-0.0018	0.0893	0.0675	-0.0699	-0.0293	-0.0274
	(-0.03)	(1.20)	(0.90)	(-0.85)	(-0.42)	(-0.66)
G4F α	0.0619	0.1531	0.1205	0.0145	0.0495	-0.0123
	(0.52)	(1.19)	(0.97)	(0.12)	(0.43)	(-0.32)
3F NA α	-0.2060	-0.1157	-0.1561	-0.2548	-0.2372	-0.0311
	(-1.01)	(-0.54)	(-0.76)	(-1.19)	(-1.15)	(-0.79)
			Return month t+3 (%)			
Average	3.5815***	3.5930***	3.6175***	3.4512***	3.4833***	-0.0982
	(4.70)	(4.69)	(4.78)	(4.54)	(4.71)	(-1.07)
CAPM α_{MSCI}	0.4313**	0.4050**	0.4272**	0.2587	0.3280*	-0.1033
	(2.41)	(2.14)	(2.30)	(1.26)	(1.84)	(-1.07)
G4F α	0.2669	0.2256	0.2993	0.1770	0.2511	-0.0158
	(1.01)	(0.81)	(1.13)	(0.62)	(0.97)	(-0.19)
3F NA α	-0.6679	-0.6980	-0.6273	-0.7811	-0.6904	-0.0225
	(-1.15)	(-1.15)	(-1.06)	(-1.24)	(-1.17)	(-0.27)

Table V: **Follower pension funds and portfolio performance**
In Panel A, I present the summary statistics of $R^2_{n,t}$: the indicator of the power of the all other pension funds' demand in predicting pension fund n's demand. $R^2_{n,t}$ measures the extent to which pension fund n follows other pension funds, and it is estimated following the steps outlined in Section III. Pension funds with high $R^2_{n,t}$ are defined as follower pension funds. Panel B presents the performance of pension fund quintile portfolios formed based on $R^2_{n,t}$. The quintile portfolios are formed at the end of each month from February 2009 to December 2018 and held for one or three months. I report equally weighted returns for each quintile portfolio over the next month and quarter (cumulative three-month returns). Quintile 5 is the portfolio of follower pension funds. Quintile 1 is the portfolio of non-followers. I also compute the risk-adjusted returns based on the CAPM and the Fama and French (2012) global size, value, and momentum factors as well as North-American size and value factors. The risk-adjusted returns are the intercept from a time-series regression of the quintile portfolios excess returns over the U.S. one month T-bill rate on the risk factors. The CAPM market return is given by the monthly total return on the MSCI All Country World Index. For the time-series regression on North-American factors the market risk premium is the return on the region's value-weighted market portfolio minus the U.S. one month T-bill rate. All factors are converted into euro returns. The t-statistics are in parentheses and are computed using Newey-West standard errors with three lags. The * indicates statistical significance at the 10% level, ** at the % 5 percent, and *** at the1% level.

	Panel A: Summary statistics of the follower pension funds measure					
	mean	sd	p5	p25	p75	p95
$R^2_{n,t}$	0.0401	0.1269	0.0000	0.0008	0.0193	0.1827
	Panel B: Follower pension funds and portfolio performance					
Quintile	(1)	(2)	(3)	(4)	(5)	5-1
Avg. R^2_t	0.0002	0.0015	0.0052	0.0174	0.1843	0.1840
	Return month t+1 (%)					
Average	1.1756***	1.1175***	1.0996***	1.1203***	1.0624***	-0.1132**
	(4.10)	(3.86)	(3.80)	(3.78)	(3.82)	(-2.38)
CAPM α_{MSCI}	0.0683	0.0136	-0.0210	0.0035	-0.0489	-0.1172**
	(0.95)	(0.18)	(-0.29)	(0.05)	(-0.57)	(-2.27)
G4F α	0.1458	0.0732	0.0416	0.0632	0.0474	-0.0985*
	(1.27)	(0.59)	(0.35)	(0.49)	(0.38)	(-1.98)
3F NA α	-0.1350	-0.1904	-0.2311	-0.2095	-0.2351	-0.1001**
	(-0.66)	(-0.88)	(-1.11)	(-0.96)	(-1.14)	(-2.01)
	Return month t+3 (%)					
Average	3.5990***	3.6001***	3.5860***	3.4780***	3.3830***	-0.2159**
	(4.65)	(4.79)	(4.75)	(4.55)	(4.60)	(-2.08)
CAPM α_{MSCI}	0.3621**	0.4523**	0.4253**	0.2905	0.2348	-0.1273
	(1.98)	(2.45)	(2.22)	(1.57)	(1.09)	(-1.24)
G4F α	0.2720	0.3102	0.1962	0.1660	0.2510	-0.0210
	(1.04)	(1.15)	(0.69)	(0.62)	(0.91)	(-0.22)
3F NA α	-0.7251	-0.6022	-0.6828	-0.7699	-0.6827	0.0424
	(-1.20)	(-0.99)	(-1.14)	(-1.25)	(-1.12)	(0.42)

Table VI: **Return comparison between leaders and followers**

The first four columns of this table report the average and risk adjusted returns of the quintile portfolios of leader, non-leader, follower and non-follower pension funds from Table IV and V. Next I compute the return difference between the portfolio of leaders and the portfolio of followers; the return difference between the portfolio of leaders and the portfolio of non-followers; the return difference between the portfolio of non-leaders and the portfolio of followers; the return difference between the portfolio of non-leaders and the portfolio of non-followers. The t-statistics are in parentheses and are computed using Newey-West standard errors with three lags. The * indicates statistical significance at the 10% level, ** at the % 5 percent, and *** at the1% level.

	PW(5)	PW(1)	$R^2(5)$	$R^2(1)$	PW(5)-$R^2(5)$	PW(5)-$R^2(1)$	PW(1)-$R^2(5)$	PW(1)-$R^2(1)$
				Return month t+1 (%)				
Average	1.0841***	1.1016***	1.0624***	1.1756***	0.0218	-0.0914**	0.0392	-0.0740*
	(3.84)	(3.82)	(3.82)	(4.10)	(0.50)	(-2.56)	(0.77)	(-1.92)
CAPM α_{MSCI}	-0.0293	-0.0018	-0.0489	0.0683	0.0197	-0.0975***	0.0471	-0.0701*
	(-0.42)	(-0.03)	(-0.57)	(0.95)	(0.40)	(-2.84)	(0.82)	(-1.74)
G4F α	0.0495	0.0619	0.0474	0.1458	0.0022	-0.0963***	0.0145	-0.0840**
	(0.43)	(0.52)	(0.38)	(1.27)	(0.04)	(-2.95)	(0.25)	(-2.19)
3F NA α	-0.2372	-0.2060	-0.2351	-0.1350	-0.0020	-0.1022***	0.0291	-0.0710*
	(-1.15)	(-1.01)	(-1.14)	(-0.66)	(-0.04)	(-3.15)	(0.52)	(-1.74)
				Return month t+3 (%)				
Average	3.4833***	3.5815***	3.3830***	3.5990***	0.1002	-0.1157	0.1985*	-0.0175
	(4.71)	(4.70)	(4.60)	(4.65)	(1.18)	(-1.32)	(1.68)	(-0.23)
CAPM α_{MSCI}	0.3280*	0.4313**	0.2348	0.3621**	0.0933	-0.0341	0.1965	0.0692
	(1.84)	(2.41)	(1.09)	(1.98)	(1.05)	(-0.40)	(1.58)	(1.08)
G4F α	0.2511	0.2669	0.2510	0.2720	0.0001	-0.0209	0.0159	-0.0050
	(0.97)	(1.01)	(0.91)	(1.04)	(0.00)	(-0.25)	(0.14)	(-0.09)
3F NA α	-0.6904	-0.6679	-0.6827	-0.7251	-0.0078	0.0346	0.0147	0.0572
	(-1.17)	(-1.15)	(-1.12)	(-1.20)	(-0.08)	(0.39)	(0.13)	(0.90)

Table VII: **Determinants of leadership among pension funds**
The table presents in column (1), (3), (5), and (6) the estimated coefficients from panel regressions of $PW_{m,t}$, the measure for leader pension funds, on pension fund characteristics. Also, the table presents in columns (2), (4), (6), and (8) the estimated coefficients form logit regressions of "Leader" that is a binary variable that equals one if a pension fund m falls within the 5^{th} quintile of $PW_{m,t}$ on pension fund characteristics. The types of pension funds are the industry-wide pension fund and corporate pension fund, the omitted category is pension asset management firms. Log size is the natural logarithm of the total equity portfolio of the pension fund. Turnover is the turnover ratio of the pension funds computed as in Brennan and Cao (1997). Flow is the pension fund flow in the previous month. Return$_{t-1}$ is the previous month's gross return of the pension fund. All models are estimated with month fixed effect and standard errors clustered at the pension fund level. The t-statistics are in parentheses. The * indicates statistical significance at the 10% level, ** at the % 5 level, and *** at the 1% level.

	Developed markets		Emerging markets		Large cap		Small cap	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	PW$_{m,t}$	Leader	PW$_{m,t}$	Leader	PW$_{m,t}$	Leader	PW$_{m,t}$	Leader
Corporate Pf.	0.008	0.297	0.015*	0.549**	0.011	0.431*	0.005	-0.028
	(0.75)	(1.10)	(1.78)	(1.99)	(1.14)	(1.84)	(0.49)	(-0.09)
Industry-wide Pf.	0.029**	0.882***	0.008	0.074	0.031***	0.857***	-0.012	-0.572
	(2.17)	(2.68)	(1.19)	(0.29)	(2.90)	(3.21)	(-1.09)	(-1.32)
Log size	-0.015***	-0.229***	0.004	0.163*	-0.015***	-0.229***	0.019***	0.599***
	(-3.11)	(-2.64)	(1.24)	(1.69)	(-3.63)	(-2.66)	(8.14)	(5.89)
Turnover	-0.058***	-1.478*	-0.055**	-1.808	-0.063***	-1.989*	-0.022	-1.144
	(-3.10)	(-1.78)	(-2.45)	(-1.50)	(-2.77)	(-1.67)	(-1.24)	(-0.97)
Flow	0.001	-0.490	-0.020*	0.230	0.014	0.116	0.033*	1.303
	(0.08)	(-0.73)	(-1.69)	(0.30)	(0.92)	(0.19)	(1.84)	(1.05)
Return$_{t-1}$	0.143	-0.346	-0.173	-1.659	0.225*	1.275	0.077	-4.967
	(1.38)	(-0.12)	(-1.40)	(-0.39)	(1.90)	(0.33)	(0.78)	(-0.90)
Constant	0.372***	1.166	0.054	-3.973***	0.385***	1.080	-0.133***	-9.628***
	(6.03)	(1.02)	(1.07)	(-2.80)	(7.09)	(0.93)	(-4.17)	(-6.33)
Observations	5089	5090	3566	3714	4955	4964	3391	3519
R^2	0.146		0.165		0.155		0.253	
Pseudo R^2		0.025		0.018		0.025		0.099

Table VIII: **Determinants of follower pension funds**

The table presents columns (1), (3), (5), and (7) the estimated coefficients from panel regressions of R^2_n, the follower measure, on pension fund characteristics. Also, the table presents in columns (2), (4), (6), and (8) the estimate coefficients from logit regressions of "Follower" that is a binary variable that equals one if pension fund n falls within the 5^{th} quintile of R^2_n on pension fund characteristics. The types of pension funds are the industry-wide pension fund and the corporate pension fund, the omitted category is pension asset management firms. Log size is the natural logarithm of the total equity portfolio of the pension fund. Turnover, is the turnover ratio of the pension funds computed as in Brennan and Cao (1997). Flow is the pension fund flow in the previous month. Return_{t-1} is the previous month's gross return of the pension fund. All models are estimated with month fixed effects and standard errors clustered at the pension fund level. The t-statistics are in parentheses, The * indicates statistical significance at the 10% level, ** at the % 5 level, and *** at the 1% level.

	Developed markets		Emerging markets		Large cap		Small cap	
	(1) $R^2_{n,t}$	(2) Follower	(3) $R^2_{n,t}$	(4) Follower	(5) $R^2_{n,t}$	(6) Follower	(7) $R^2_{n,t}$	(8) Follower
Corporate Pf.	-0.000	0.082	0.069	0.616^{*}	0.052^{**}	0.530	-0.049	-0.289
	(-0.01)	(0.22)	(1.42)	(1.75)	(2.24)	(1.49)	(-1.00)	(-0.78)
Industry-wide Pf.	0.006	0.190	0.015	0.041	0.025	0.333	-0.006	-0.048
	(0.27)	(0.48)	(0.33)	(0.09)	(1.13)	(0.89)	(-0.12)	(-0.13)
Log size	-0.014^{***}	-0.422^{***}	-0.085^{***}	-0.902^{***}	-0.028^{***}	-0.485^{***}	-0.067^{***}	-0.581^{***}
	(-3.86)	(-4.26)	(-5.14)	(-7.67)	(-3.72)	(-4.72)	(-4.74)	(-3.92)
Turnover	-0.153^{***}	-18.370^{***}	-0.318^{*}	-3.836^{*}	-0.251^{***}	-16.032^{***}	-0.253^{***}	-2.575^{*}
	(-4.74)	(-4.75)	(-1.72)	(-1.70)	(-4.43)	(-4.87)	(-2.92)	(-1.80)
Flow	0.027	-0.693	0.008	-0.024	0.045	-2.452	0.039	0.952
	(1.53)	(-0.28)	(0.09)	(-0.03)	(1.49)	(-1.15)	(0.92)	(1.57)
Return_{t-1}	0.304	1.149	-0.461	0.486	-0.137	-2.641	-0.207	0.039
	(1.19)	(0.34)	(-0.77)	(0.09)	(-0.28)	(-0.63)	(-0.35)	(0.01)
Constant	0.231^{***}	4.190^{***}	1.445^{***}	10.031^{***}	0.432^{***}	5.045^{***}	1.091^{***}	6.397^{***}
	(4.95)	(3.38)	(6.72)	(6.82)	(4.25)	(4.00)	(6.01)	(3.40)
Observations	5273	5273	4500	4418	5244	5244	4732	4732
R^2	0.053		0.182		0.104		0.132	
Pseudo R^2		0.073		0.166		0.092		0.097

Table IX: **Herding and pension fund future performance - Predictive regression**
In columns (1)-(4), the table presents the coefficients from predictive panel regressions that estimate the relation between future pension funds' performance and the measures for leader pension funds (PW_m and the dummy variable "Leader" that equals one if a pension fund n falls within the 5^{th} quintile of PW_m). In columns (5)-(8), the table presents the coefficients from predictive panel regressions that estimate the relation between future pension funds' performance and the measures for follower pension funds (R_n^2 and the dummy variable "Follower" that equals one if a pension fund n falls within the 5^{th} quintile of R_n^2). The dependent variable is the global four-factor alpha that is estimated with rolling-window regressions over the previous three years of the excess return (over the U.S. one month T-bill rate) of each pension fund on the global market, size, value, and momentum factors from Fama and French (2012). The panel regressions include control variables for the type of pension fund, lag pension fund size, lag turnover, and lag flow. The types of pension funds are the industry-wide pension fund and corporate pension fund, the omitted category is pension asset management firms. All models are estimated with month fixed effects and standard errors clustered at the pension fund level. The t-statistics are in parenthesis. The * indicates statistical significance at the 10% level, ** at the 5 % level, and *** at the 1% level.

	(1) G4F α_t	(2) G4F α_t	(3) G4F α_t	(4) G4F α_t	(5) G4F α_t	(6) G4F α_t	(7) G4F α_t	(8) G4F α_t
$\mathrm{PW}_{m,t-1}$	-0.0016*	-0.0012						
	(-1.75)	(-1.51)						
Leader_{t-1}			-0.0002	-0.0002				
			(-1.22)	(-1.58)				
$R^2_{n,t-1}$					-0.0023***	-0.0020***		
					(-4.59)	(-2.95)		
$\mathrm{Follower}_{t-1}$							-0.0006***	-0.0005**
							(-2.87)	(-2.32)
Corporate Pf.		0.0011**		0.0011**		0.0011**		0.0011**
		(2.09)		(2.07)		(2.09)		(2.10)
Industry-wide Pf.		0.0009		0.0008		0.0008		0.0008
		(1.52)		(1.49)		(1.41)		(1.42)
Log size_{t-1}		0.0001		0.0001		0.0001		0.0001
		(1.02)		(1.24)		(1.25)		(1.19)
$\mathrm{Turnover}_{t-1}$		-0.0015*		-0.0015*		-0.0016**		-0.0017**
		(-1.93)		(-1.93)		(-2.12)		(-2.29)
Flow_{t-1}		-0.0012		-0.0012*		-0.0014*		-0.0014*
		(-1.62)		(-1.71)		(-1.85)		(-1.86)
Constant	0.0057***	0.0033*	0.0055***	0.0029*	0.0056***	0.0029*	0.0056***	0.0030*
	(25.36)	(1.91)	(23.90)	(1.78)	(23.22)	(1.76)	(23.43)	(1.83)
Observations	3296	3225	3296	3225	3368	3265	3368	3265
R^2	0.422	0.475	0.419	0.475	0.427	0.477	0.428	0.478

Table X: **Aggregate herding - buyer if increased return-adjusted portfolio weight**
For each security and month between January 2009 and December 2018, I compute the fraction of pension funds (Pf) that increase their return-adjusted portfolio weight of the security. A pension fund is defined as increasing their return-adjusted portfolio weight (buyer) if their return-adjusted month-end portfolio weight is greater than their return-adjusted beginning-of-month portfolio weight, as described in Equation (10). Each month, I standardize both the fraction of pension funds that increase their return-adjusted portfolio weight and the lag fraction of pension funds that increase their return-adjusted portfolio weight to have a zero mean and a unit variance. Then, I estimate a cross-sectional regression (across J securities) of the standardized fraction of pension funds that increase their return-adjusted portfolio weight on the lag standardized fraction of pension funds increase their return-adjusted portfolio weight for each month: Equation (3). Next, I decompose the regression coefficient into the portion of correlations that arises from pension funds following themselves and following each other i.e., Equation (4). The first column presents the time-series average of 119 correlation coefficients. The second and third column give the time-series average of the portion of correlations that arises from pension funds following themselves and each other's changes in the return-adjusted portfolio weights. The fourth column report the time-series average of the R^2 of the 119 cross-sectional regressions. The associated t-statistics are reported in parentheses. The * indicates statistical significance at the 10% level, ** at the % 5 level, and *** at the 1% level. Panels A, B, and C give the results when limiting the sample to securities with at least 3, 5 or 10 trading funds.

	Time-series avg. β coeff.	Pf. following their own weights	Pf. following others' weights	Avg. R^2
Panel A: Securities with $\geq$ 3 traders	0.1406***	0.0911***	0.0495***	0.0508***
	(8.68)	(4.91)	(3.17)	(9.84)
Panel B: Securities with $\geq$ 5 traders	0.1551***	0.0953***	0.0599***	0.0414***
	(12.80)	(5.57)	(3.72)	(9.91)
Panel C: Securities with $\geq$ 10 traders	0.1884***	0.0983***	0.0901***	0.0449***
	(21.06)	(10.16)	(9.05)	(14.01)

Table XI: **Aggregate herding and style investing**
For each security and month between January 2009 and December 2018, I compute the fraction of pension funds (Pf) that increase their position in the security, as in Equation (1). Pension funds are defined as increasing their position (buyers) if they hold a greater number of split-adjusted securities at the end of the month than they held at the beginning. Each month I regress the standardized fraction of pension funds that buy security j on the standardized lag fraction of pension funds that buy security j and the standardized lag return of j, or the standardized lag market capitalization or the standardized lag book-to-market ratio: Equation (12). Adding these stock-level variables allows to correct for style investing such as: momentum, large or value stocks. Standardization (i.e., each month all variables are scaled to have a zero mean and a unit variance) allows to directly compare the coefficients that are associated with the independent variables over different months. Panel A presents the time-series average of the 119 monthly cross-sectional regression coefficients, when limiting the sample to securities in at least three traders. The associated t-statistics are in parentheses. Panel B limits the sample to securities with at least five trading funds, and Panel C limits the sample to securities with in at least ten trading funds. The * indicates statistical significance at the 10% level, ** at the % 5 level, and *** at the 1% level.

	Time-series avg. β coeff.	Time-series avg. lag return	Time-series avg. lag mkt. cap.	Time-series avg. lag book-to-mkt
Panel A: Securities $\geq$ 3 trader	0.1970***	-0.0063		
	(33.63)	(-1.39)		
	0.1971***		0.0045	
	(33.97)		(0.84)	
	0.1969***			0.0053
	(33.38)			(1.07)
	0.1965***	-0.0066	0.0054	0.0054
	(34.11)	(-1.53)	(1.03)	(1.15)
Panel B: Securities $\geq$ 5 trader	0.1943***	-0.0164***		
	(29.62)	(-3.08)		
	0.1951***		-0.0024	
	(29.98)		(-0.39)	
	0.1945***			0.0205***
	(29.13)			(3.51)
	0.1945***	-0.0167***	-0.0001	0.0190***
	(29.91)	(-3.35)	(-0.02)	(3.44)
Panel C: Securities $\geq$ 10 trader	0.1979***	-0.0415***		
	(21.65)	(-4.99)		
	0.1992***		-0.0453***	
	(21.72)		(-5.46)	
	0.1957***			0.0622***
	(21.32)			(8.57)
	0.1950***	-0.0379***	-0.0395***	0.0522***
	(21.59)	(-4.72)	(-4.91)	(7.57)

Appendix A.

Returns on security positions are computed following the modified Dietz (1966) method:

$$R_{n,j,t} = \frac{V_{n,j,t} - Trade_{n,j,t} - EX_{n,j,t} - V_{n,j,t-1}}{V_{n,j,t-1} * 0.5(Trade_{n,j,t})} \tag{A1}$$

where $V_{n,j,t}$ is the value of the position in security j of pension fund n in month t. $Trade_{n,j,t}$ represents the net value traded of security j by pension fund n during month t: total purchases minus total sells. $EX_{n,j,t}$ is the change in value of the position in j due to exchange rate changes. $V_{n,j,t-1}$ is the value of the position in security j of pension fund n in month $t-1$, which corresponds to the value of the position at the beginning of month t. By multiplying $Trade_{n,j,t}$ times 0.5 in the denominator of Equation (A1), I assume that transactions are on average executed halfway during the month. $R_{n,j,t}$ is therefore the return on the position in each security. Pension funds' total return are computed as weighted average of the returns on each position, where weights are the share of each security in the pension fund's portfolio.

Appendix B.

Appendix A. Returns of leaders in markets with high information asymmetries

In this appendix, I perform the quintile portfolio analysis to examine the difference in performance of leader pension funds and non-leader pension funds in markets with high information asymmetries. Therefore, I focus on small capitalization securities opposed to large capitalization securities, and emerging market securities opposed to developed market securities. To perform this analysis, each month I sort all the securities with at least three trading funds into five quintiles based on their beginning of the month market capitalization. I then estimate Equation (5) and Equation (7) for the bottom and top quintiles of securities separately. Next, I compute $PW_{m,t}$ for both the bottom and top quintiles of market capitalization. Hence, I identify leader and non-leader pension funds in small capitalization securities, and leader and non-leader pension funds in large capitalization securities. Then, I form quintile portfolios at the end of each month by sorting pension funds into five portfolios based on $PW_{m,t}$. Next, I compute equally weighted posterior returns for each quintile portfolio. In this analysis, the returns of each pension fund correspond to the value-weighted[27] returns of all small or large capitalization securities in the pension fund's portfolio. The results are displayed in Table XII.

Similarly, I examine the difference in performance between leader pension funds and non-leader pension funds only focusing on the share of pension funds' portfolios invested in developed and emerging markets. To perform this analysis, I estimate Equation (5) and Equation (7) separately for developed and emerging markets securities. Next, I identify the leader and non-leader pension funds in the two markets by computing $PW_{m,t}$. As before, I construct five quinitile portfolios based

[27]Weights here represent the value of the position in each security over the total equity portfolio of each pension fund

on $PW_{m,t}$ and I compute equally weighted posterior returns for each quintile portfolio. The results are reported in Table XIII and show that leader pension funds do not perform significantly better than non-leader pension funds in either developed or emerging stock markets.

Appendix B. Returns of followers in markets with high information asymmetries

Here, I examine the difference in performances between follower and non-follower pension funds only focusing on small capitalization and large capitalization securities. To perform this analysis, I sort, each month, all the securities with at least three trading funds into five quintiles based on their beginning-of-month market capitalization. I then estimate Equation (9) for the bottom and top quintile of securities separately. Next, I compute R_n^2 for both the bottom and top quintiles of market capitalization. Hence, I identify follower and non-follower pension in small capitalization securities, as well as follower and non-follower pension funds in large capitalization securities. Then, I form quintile portfolios at the end of each month by sorting pension funds into five portfolios based on R_n^2. Next, I compute equally weighted posterior returns for each quintile portfolio. In this analysis, the returns of each pension fund correspond to the value-weighted returns of all small or large capitalization securities in the pension fund's portfolio. The results are reported in Table XIV.

Similarly, I examine the difference in performances between follower pension funds and non-follower pension funds only focusing on the share of pension funds' portfolios invested in developed and emerging markets. To perform this analysis, I estimate Equation (9) separately for developed and emerging economies. Next, I identify follower and non-follower pension funds in the two markets by measuring R_n^2 . As before, I construct five quinitile portfolios based on R_n^2, and I compute equally weighted posterior returns for each quintile portfolio. The results are displayed in Table XV and show that follower pension funds underperform non-follower pension funds by 0.23% on a monthly basis. This analysis integrates the findings of Section IV.A and relies on the same method used in that section.

Table XII: **Leader pension funds and portfolio performance by security size**
Each month between January 2009 and December 2018, I sort all securities with at least three trading funds into five quintiles based on their beginning-of-month market capitalization. I estimate Equation (5) and Equation (7) by limiting the sample to the quintile of securities with either the smallest market capitalization or the largest market capitalization. Next, I compute $PW_{m,t}$ as in Equation (8) for the sample of securities of either small or large capitalization. In Panel A, I present the summary statistics of $PW_{m,t}$: the indicator of the power of a pension fund's demand for small capitalization securities in predicting the future demand for small capitalization securities of other pension funds. $PW_{m,t}$ is estimated following the steps outlined in Section III and captures the extent to which pension funds are followed by others. Pension funds with high $PW_{m,t}$ are defined as leader pension funds (in the market of small capitalization securities). Panel B presents the performance of quintile portfolios of pension funds that are formed on the basis of this measure for leader pension funds. The quintile portfolios are formed at the end of each month from February 2009 to December 2018 and held for one month. I report the average posterior-month equally weighted returns of the pension funds' portfolios. Quintile 5 is the portfolio of leader pension funds. Quintile 1 is the portfolio of non-leaders. I also compute the risk-adjusted returns based on the CAPM and the Fama and French (2012) global size, value, and momentum factors as well as North-American size and value factors. The risk-adjusted returns are the intercept from a time-series regression of the quintile portfolios excess returns over the U.S. one month T-bill rate on the risk factors. The CAMP alphas for small cap securities are estimated using the MSCI AC World Small Cap Index as the market return. In Panel B, I present the summary statistics of $PW_{m,t}$ and the quintile portfolio returns for leader and non-leader pension funds in the market of large capitalization securities. The CAMP alphas for large cap securities are estimated using the MSCI All Country World Index as the market return. All factors are converted into euro returns. The t-statistics are in parentheses and are computed using Newey-West standard errors with three lags. The * indicates statistical significance at the 10% level, ** at the % 5 percent, and *** at the1% level.

	Panel A: Leader pension funds and portfolio performance - small stocks					
Quintile	(1)	(2)	(3)	(4)	(5)	5-1
Avg. PW_t	0.0300	0.0693	0.1057	0.1411	0.1957	0.1657
			Return month t+1 (%)			
Average	0.0236*	0.0353*	0.0274*	0.0247*	0.0283**	0.0047
	(1.78)	(1.94)	(1.71)	(1.71)	(2.09)	(0.56)
CAPM $\alpha_{MSCI-small-Cap}$	-0.5018**	-0.4977**	-0.4992**	-0.5012**	-0.4981**	0.0037
	(-2.17)	(-2.18)	(-2.18)	(-2.19)	(-2.18)	(0.41)
G4F α	-0.0214	-0.0140	-0.0220	-0.0230	-0.0175	0.0038
	(-0.21)	(-0.14)	(-0.21)	(-0.23)	(-0.17)	(0.46)
3F NA α	-0.2116	-0.2050	-0.2098	-0.2121	-0.2076	0.0040
	(-1.44)	(-1.38)	(-1.39)	(-1.43)	(-1.41)	(0.44)
	Panel B: Leader pension funds and portfolio performance - large stocks					
Avg. PW_t	0.0860	0.1373	0.1782	0.2254	0.3095	0.2235
			Return month t+1 (%)			
Average	0.7150***	0.6836***	0.7202***	0.7166***	0.7052***	-0.0098
	(4.35)	(3.90)	(4.05)	(4.13)	(3.95)	(-0.28)
CAPM α_{MSCI}	-0.1604	-0.2070*	-0.1734	-0.1637	-0.1949*	-0.0345
	(-1.34)	(-1.85)	(-1.51)	(-1.44)	(-1.73)	(-1.05)
G4F α	0.0796	0.0311	0.0707	0.0705	0.0439	-0.0356
	(0.82)	(0.31)	(0.72)	(0.71)	(0.44)	(-1.10)
3F NA α	-0.1664	-0.2198	-0.1870	-0.1712	-0.2123	-0.0458
	(-1.05)	(-1.34)	(-1.13)	(-1.06)	(-1.33)	(-1.31)

Table XIII: **Leader pension funds and portfolio performance by geographical area**
Each month between January 2009 and December 2018, I sort all securities with at least three trading funds into two groups based on their geographical area: developed and emerging markets. I estimate Equation (5) and Equation (7) by limiting the sample to the securities that belong to either developed or emerging markets. Next, I compute $PW_{m,t}$ as in Equation (8) for each of the two samples. In Panel A, I present the summary statistics of $PW_{m,t}$: the indicator of the power of a pension fund's demand for developed markets securities in predicting the future demand for developed markets securities of other pension funds. $PW_{m,t}$ is estimated following the steps outlined in Section III and captures the extent to which pension funds are followed by others. Pension funds with high $PW_{m,t}$ are defined as leader pension funds (in developed markets securities). Panel B presents the performance of quintile portfolios of pension funds that are formed on the basis of this measure for leader pension funds. The quintile portfolios are formed at the end of each month from February 2009 to December 2018 and held for one month. I report the average posterior-month equally weighted returns of the pension funds' portfolios. Quintile 5 is the portfolio of leader pension funds. Quintile 1 is the portfolio of non-leaders. I also compute the risk-adjusted returns based on the CAPM and the Fama and French (2012) global size, value, and momentum factors as well as North-American size and value factors. The risk-adjusted returns are the intercept from a time-series regression of the quintile portfolios excess returns over the U.S. one month T-bill rate on the risk factors. The CAMP alphas for developed markets securities are estimated using the MSCI All Country World Index as the market return. In Panel B, I present the summary statistics of $PW_{m,t}$ and the quintile portfolio returns for leader and non-leader pension funds in emerging market securities. The CAMP alphas for emerging markets securities are estimated using the MSCI Emerging Markets Index as the market return. All factors are converted into euro returns. The t-statistics are in parentheses and are computed using Newey-West standard errors with three lags. The * indicates statistical significance at the 10% level, ** at the % 5 percent, and *** at the1% level.

	Panel A: Leader pension funds and portfolio performance - Developed					
Quintile	(1)	(2)	(3)	(4)	(5)	5-1
Avg. PW_t	0.0900	0.1468	0.1910	0.24020	0.3216	0.2320
	Return month t+1 (%)					
Average	0.9602***	1.0146***	0.9858***	0.9536***	0.9433***	-0.0169
	(3.86)	(4.21)	(3.83)	(3.79)	(3.83)	(-0.36)
CAPM α_{MSCI}	-0.0528	-0.0008	-0.0417	-0.0779	-0.0809	-0.0281
	(-0.69)	(-0.01)	(-0.48)	(-0.94)	(-0.97)	(-0.60)
G4F α	0.0474	0.1086	0.0606	0.0429	0.0400	-0.0075
	(0.43)	(1.00)	(0.50)	(0.39)	(0.36)	(-0.17)
3F NA α	-0.2110	-0.1496	-0.2015	-0.2272	-0.2306	-0.0196
	(-1.14)	(-0.83)	(-1.09)	(-1.15)	(-1.20)	(-0.43)
	Panel B: Leader pension funds and portfolio performance -Emerging					
Avg. PW_t	0.0571	0.1015	0.1323	0.1650	0.2190	0.1619
	Return month t+1 (%)					
Average	0.2426***	0.2290***	0.2720***	0.2569***	0.2680**	0.0254
	(3.23)	(2.75)	(2.95)	(3.04)	(2.50)	(0.38)
CAPM $\alpha_{MSCI-EM}$	-0.2393	-0.2612	-0.2259	-0.2412	-0.2382	0.0011
	(-1.28)	(-1.47)	(-1.26)	(-1.34)	(-1.34)	(0.02)
G4F α	0.0573	0.0093	0.0271	0.0330	0.0438	-0.0135
	(0.52)	(0.09)	(0.23)	(0.27)	(0.36)	(-0.21)
3F NA α	-0.1372	-0.1927	-0.1821	-0.1834	-0.1668	-0.0296
	(-0.84)	(-1.22)	(-1.06)	(-1.07)	(-1.05)	(-0.50)

Table XIV: **Follower pension funds and portfolio performance by security size**
Each month between January 2009 and December 2018, I sort all securities with at least three trading funds into five quintiles based on their beginning-of-month market capitalization. I estimate Equation (9) for each pension fund $n's$ demand by limiting the sample to the quintile of securities with either the smallest market capitalization or the largest market capitalization. For each pension fund, I obtain $R^2_{n,t}$ from Equation (9). In Panel A, I present the summary statistics of $R^2_{n,t}$: the indicator of the power of the all other pension funds' demand for small capitalization securities in predicting pension fund n's demand for small capitalization securities. $R^2_{n,t}$ measures the extent to which pension fund n follows other pension funds, and it is estimated following the steps outlined in Section III. Pension funds with high $R^2_{n,t}$ are defined as follower pension funds. Panel B presents the performance of pension fund quintile portfolios formed based on $R^2_{n,t}$. The quintile portfolios are formed at the end of each month from February 2009 to December 2018 and held for one month. I report the average posterior-month equally weighted returns of the pension fund portfolios. Quintile 5 is the portfolio of follower pension funds. Quintile 1 is the portfolio of non-followers. I also compute the risk-adjusted returns based on the CAPM and the Fama and French (2012) global size, value, and momentum factors as well as North-American size and value factors. The risk-adjusted returns are the intercept from a time-series regression of the quintile portfolios excess returns over the U.S. one month T-bill rate on the risk factors. The CAMP alphas for small cap securities are estimated using the MSCI AC World Small Cap Index as the market return. In Panel B, I present the summary statistics of $R^2_{n,t}$ and the quintile portfolio returns for follower and non-follower pension funds in large market capitalization securities. The CAMP alphas for large cap securities are estimated using the MSCI All Country World Index as the market return. All factors are converted into euro returns. The t-statistics are in parentheses and are computed using Newey-West standard errors with three lags. The * indicates statistical significance at the 10% level, ** at the % 5 percent, and *** at the1% level.

	Panel A: Follower pension funds and portfolio performance - small stocks					
Quintile	(1)	(2)	(3)	(4)	(5)	5-1
Avg. R^2_t	0.0011	0.0090	0.0390	0.1781	0.7264	0.7253
	Return month t+1 (%)					
Average	0.0212*	0.0327**	0.0273**	0.0170	0.0150	-0.0062
	(1.77)	(2.18)	(2.17)	(1.16)	(1.35)	(-0.87)
CAPM $\alpha_{MSCI-small-Cap}$	-0.5024**	-0.4964**	-0.4995**	-0.5083**	-0.5026**	-0.0002
	(-2.18)	(-2.17)	(-2.17)	(-2.22)	(-2.18)	(-0.03)
G4F α	-0.0222	-0.0162	-0.0195	-0.0311	-0.0210	0.0012
	(-0.22)	(-0.16)	(-0.19)	(-0.30)	(-0.20)	(0.15)
3F NA α	-0.2119	-0.2072	-0.2089	-0.2177	-0.2104	0.0015
	(-1.45)	(-1.40)	(-1.41)	(-1.46)	(-1.44)	(0.19)
	Panel B: Follower pension funds and portfolio performance - large stocks					
Avg. R^2_t	0.0005	0.0033	0.0118	0.0450	0.3641	0.3636
	Return month t+1 (%)					
Average	0.6876***	0.7031***	0.7197***	0.6948***	0.6646***	-0.0230
	(4.03)	(4.04)	(4.27)	(3.99)	(3.71)	(-0.57)
CAPM α_{MSCI}	-0.1962*	-0.1881	-0.1582	-0.1927*	-0.2303*	-0.0341
	(-1.72)	(-1.62)	(-1.38)	(-1.73)	(-1.83)	(-0.80)
G4F α	0.0443	0.0562	0.0713	0.0499	0.0251	-0.0192
	(0.43)	(0.58)	(0.74)	(0.55)	(0.24)	(-0.39)
3F NA α	-0.2040	-0.1994	-0.1657	-0.2005	-0.2282	-0.0241
	(-1.27)	(-1.23)	(-1.05)	(-1.29)	(-1.29)	(-0.49)

Table XV: **Follower pension funds and portfolio performance by geographical area**
At the beginning of each month between January 2009 and December 2018, I sort all securities with at least three trading funds into two groups based on their geographical area: developed and emerging markets. I estimate Equation (9) for each pension fund $n's$ demand by limiting the sample to either securities from developed markets or securities from emerging markets. For each pension fund I obtain $R^2_{n,t}$ from Equation (9). In Panel A, I present the summary statistics of $R^2_{n,t}$: the indicator of the power of the all other pension funds' demand for developed markets securities in predicting pension fund n's demand for developed markets securities. $R^2_{n,t}$ measures the extent to which pension fund n follows other pension funds, and it is estimated following the steps outlined in Section III. Pension funds with high $R^2_{n,t}$ are defined as follower pension funds. Panel B presents the performance of pension fund quintile portfolios formed based on $R^2_{n,t}$. The quintile portfolios are formed at the end of each month from February 2009 to December 2018 and held for one month. I report the average posterior-month equally weighted returns of the pension fund portfolios. Quintile 5 is the portfolio of follower pension funds. Quintile 1 is the portfolio of non-followers. I also compute the risk-adjusted returns based on the CAPM and the Fama and French (2012) global size, value, and momentum factors as well as North-American size and value factors. The risk-adjusted returns are the intercept from a time-series regression of the quintile portfolios excess returns over the U.S. one month T-bill rate on the risk factors. The CAMP alphas for developed markets securities are estimated using the MSCI All Country World Index as the market return. In Panel B, I present the summary statistics of $R^2_{n,t}$ and the quintile portfolio returns for follower and non-follower pension funds in emerging markets securities. The CAMP alphas for emerging markets securities are estimated using the MSCI Emerging Markets Index as the market return. All factors are converted into euro returns. The t-statistics are in parentheses and are computed using Newey-West standard errors with three lags. The * indicates statistical significance at the 10% level, ** at the % 5 percent, and *** at the1% level.

	Panel A: Follower pension funds and portfolio performance - Developed					
Quintile	(1)	(2)	(3)	(4)	(5)	5-1
Avg. R^2_t	0.0002	0.0017	0.0064	0.0244	0.2424	0.2422
	Return month t+1 (%)					
Average	1.0126***	0.9806***	0.9444***	0.9762***	0.8934***	-0.1192**
	(4.11)	(3.92)	(3.71)	(3.92)	(3.65)	(-2.54)
CAPM α_{MSCI}	-0.0066	-0.0405	-0.0786	-0.0597	-0.1288	-0.1222**
	(-0.08)	(-0.52)	(-0.92)	(-0.73)	(-1.37)	(-2.33)
G4F α	0.1086	0.0684	0.0174	0.0458	0.0200	-0.0886
	(1.04)	(0.64)	(0.15)	(0.40)	(0.17)	(-1.65)
3F NA α	-0.1563	-0.1968	-0.2334	-0.2260	-0.2531	-0.0969*
	(-0.86)	(-1.05)	(-1.19)	(-1.15)	(-1.35)	(-1.86)
	Panel B: Follower pension funds and portfolio performance - Emerging					
Avg. R^2_t	0.0010	0.0079	0.0340	0.1819	0.7509	0.7499
	Return month t+1 (%)					
Average	0.2818***	0.2547***	0.1787**	0.1329***	0.0566***	-0.2251***
	(3.38)	(3.01)	(2.29)	(2.78)	(2.63)	(-2.96)
CAPM $\alpha_{MSCI-EM}$	-0.1729	-0.2089	-0.2518	-0.2726	-0.3024	-0.1295***
	(-1.00)	(-1.19)	(-1.36)	(-1.47)	(-1.49)	(-2.96)
G4F α	0.0476	0.0135	-0.0247	-0.0230	-0.0031	-0.0507
	(0.42)	(0.11)	(-0.21)	(-0.22)	(-0.03)	(-1.06)
3F NA α	-0.1731	-0.2093	-0.2513	-0.2372	-0.2145	-0.0414
	(-1.06)	(-1.28)	(-1.54)	(-1.59)	(-1.47)	(-0.76)

Appendix C.

Appendix A. Portfolio returns of over-time leader pension funds

In this appendix, I compare the returns of pension funds that exhibit the highest $PW_{m,t}$ more often with the returns of pension funds that exhibit the lowest $PW_{m,t}$ measure more often in the sample period. Namely, I compare the returns of pension funds that are more often categorized as leaders over time with the returns of pension funds that are more often categorized as non-leaders. At the end of each month, I sort pension funds into five quintiles based on the measure of the prediction power of demand, $PW_{m,t}$. Within each quintile of $PW_{m,t}$, I then sort pension funds into three terciles based on the number of months that each pension fund appears in the selected quintile of $PW_{m,t}$. For example, within quintile 5 of $PW_{m,t}$ (the quintile of leader pension funds), I sort pension funds in three terciles where the tercile 3 groups the pension funds that report a $PW_{m,t}$ that falls within quintile 5 more often. Namely, pension funds that are more often indicated as leader pension funds over time. Similarly within quintile 1 of $PW_{m,t}$, tercile 3 groups the pension funds that report a $PW_{m,t}$ that falls within quintile 1 more often. Namely, pension funds that are more often indicated as non-leader pension funds over time. This procedure generates 15 double-sorted portfolios of pension funds (15×3) Next, I compute equally-weighted returns of the double-sorted portfolio of pension funds. In Table XVI, I compare the returns of pension funds in the double-sorted portfolio 5/3 with the returns of pension funds in the double sorted portfolio 1/3. Namely, I compare the returns of pension funds that are more often categorized as leader over time with the results of pension funds that more often categorized as non-leader pension funds. In Table XVI, I also report the the risk-adjusted returns of these portfolios as intercepts from time-series regressions that use the capital asset pricing model (CAPM) the global three-factor model of Fama and French (2012) augmented with the global momentum factor and the North American market risk premium, size and value factors. There are 7 pension funds in the 5/3 portfolio, and each of them is categorized as leader in 44, 40, 39, 38, 61, 47 and 45 months out of the 119 months in the sample period. The over-time non-leader pension funds (in the 1/3 portfolio) are 5, and each of them is categorized as such in 75, 76, 59, 50 and 109 months out of 119. There is no overlap between the pension funds that are included in the double-sorted portfolio 5/3 and the double-sorted portfolio 1/3. Namely, over-time leaders do not overlap with over-time non-leaders.

Table XVI shows that over-time leaders underperform over-time non-leaders both in the month after portfolio formation and in the subsequent three months. The uderperformance is sizable although not highly statistically significant: -0.11% in the subsequent month and a cumulative three-month return of -0.33%. After risk adjustment the underperfomance becomes larger in magnitude and highly statistically significant for all specification, confirming that indeed over-time leaders perform worse than over-time non-leaders. Moreover, all leader pension funds, except one that is a fund of large corporation, are industry-wide pension funds. These results provide additional evidence supporting the hypothesis that herding can be associated to reputational concerns, as over time leaders are not better-skilled investors but are generally pension funds more exposed to the public opinion.

Appendix B. Portfolio returns of over-time follower pension funds

I apply the same methodology to compare the returns of pension funds that exhibit the highest $R^2_{n,t}$ measure more often with the returns of pension funds that exhibit the lowest $R^2_{n,t}$ measure more often in the sample period. Specifically, at the end of each month, I sort pension funds into five quintiles based on their tendency to follow others: $R^2_{n,t}$. Within each quintile of $R^2_{n,t}$, I then sort pension funds into three terciles based on the number of months that each pension fund appears in the selected quintile of $R^2_{n,t}$. For example, within quintile 5 of $R^2_{n,t}$ (the quintile of follower pension funds), I sort pension funds into three terciles where tercile 3 groups the pension funds that report a $R^2_{n,t}$ that falls within quintile 5 more often. Namely, pension funds that are more often indicated as follower pension funds over time. Similarly within quintile 1 of $R^2_{n,t}$, the tercile 3 groups the pension funds that report a $R^2_{n,t}$ that falls within quintile 1 more often. Namely, pension funds that are more often indicated as non-follower pension funds over time. Next, I compute equally-weighted returns of the double-sorted portfolio of pension funds. In Table XVII, I compare the returns of pension funds in the double-sorted portfolio 5/3 with the returns of pension funds in the double sorted portfolio 1/3. Namely, I compare the returns of pension funds that are more often categorized as follower pension funds over time with the results of pension funds that are more often categorized as non-follower pension funds. There are 7 pension funds that are more often categorized as follower pension funds (double-sorted portfolio 5/3), and each of them is categorized as such in 53, 55, 50, 47, 53, 34, 32 months out of the 119 in the sample period. The pension funds that are more often categorized as non-followers (in the 1/3 portfolio) are 9 and each of them is categorized as such in 41, 52, 35, 33, 37, 34, 43, 58, 36 out of 119. There is no overlap between the pension funds that are included in the double-sorted portfolio 5/3 and the double-sorted portfolio 1/3. Namely, over-time followers do not overlap with over-time non-followers.

Table XVII shows that over-time followers underperform over-time non-followers by 0.17% on a monthly basis and by 0.52% on a three-month basis. This result is in line with the findings of Table V and indicates once again that herding negatively affect performance, as pension funds that herd more over time systematically perform worse than pension funds that herd less over time. The results are unchanged after controlling for different risk factors.

Table XVI: Over-time leader pension funds and portfolio performance
At the end of each month, I sort pension funds into five quintiles based on the measure of the prediction power of demand, $PW_{m,t}$. Within each quintile of $PW_{m,t}$, I then sort pension funds into three terciles based on the number of months that each pension fund appears in the selected quintile of $PW_{m,t}$. Next, I compute equally-weighted returns of the double-sorted portfolio of pension funds. The double-sorted portfolios are formed at the end of each month from February 2009 to December 2018 and held for one or three months. I report equally weighted returns of the double-sorted pension fund portfolios over the next month and quarter (cumulative three-month returns). The table compares the returns of pension funds in the double-sorted portfolio 5/3 (5^{th} quintile of $PW_{m,t}$ and 3^{rd} frequency tercile) with the returns of pension funds in the double sorted portfolio 1/3 (1^{st} quintile of $PW_{m,t}$ and 3^{rd} frequency tercile). Namely, the table compares the returns of pension funds that are more often categorized as leaders over time with the results of pension funds that more often categorized as non-leaders. The table also reports the risk-adjusted returns based on the CAPM and the Fama and French's (2012) global size, value, and momentum factors as well as North-American size and value factors. The risk-adjusted returns are the intercept from a time-series regression of the double-sorted portfolios' excess returns over the U.S. one month T-bill rate on the risk factors. The CAPM market return is given by the monthly total return on the MSCI All Country World Index. For the time-series regression on North-American factors the market risk premium is the return on the region's value-weighted market portfolio minus the U.S. one month T-bill rate. All factors are converted into euro returns. The t-statistics are in parentheses and are computed using Newey-West standard errors with three lags. The * indicates statistical significance at the 10% level, ** at the % 5 percent, and *** at the1% level.

Double sorting	(1/3)	(5/3)	(5/3)-(1/3)
Avg. PW_t	0.0777	0.3338	0.2561
	Return month t+1 (%)		
Average	1.3055***	1.1924***	-0.1131
	(3.80)	(3.41)	(-1.45)
CAPM α_{MSCI}	0.1116	-0.0527	-0.1644**
	(1.50)	(-0.71)	(-2.14)
G4F α	0.1709	0.0116	-0.1593**
	(1.45)	(0.10)	(-2.06)
3F NA α	-0.0843	-0.2719	-0.1876**
	(-0.38)	(-1.15)	(-2.40)
	Return month t+3 (%)		
Average	3.7966***	3.4660***	-0.3306*
	(4.52)	(3.98)	(-1.79)
CAPM α_{MSCI}	0.5886***	0.0858	-0.5028***
	(3.68)	(0.51)	(-2.75)
G4F α	0.6052**	0.1125	-0.4927**
	(2.33)	(0.42)	(-2.26)
3F NA α	-0.5336	-1.0575	-0.5239**
	(-0.92)	(-1.59)	(-2.40)

Table XVII: Over-time follower pension funds and terciles of portfolio performance At the end of each month, I sort pension funds into five quintiles based on the herding measure $R^2_{n,t}$. Within each quintile of $R^2_{n,t}$, I then sort pension funds into three terciles based on the number of months that each pension fund appears in the selected quintile of $R^2_{n,t}$. Next, I compute equally-weighted returns of the double-sorted portfolio of pension funds. The double-sorted portfolios are formed at the end of each month from February 2009 to December 2018 and held for one or three months. I report equally weighted returns of the double-sorted pension fund portfolios over the next month and quarter (cumulative three-month returns). The table compares the returns of pension funds in the double-sorted portfolio 5/3 (5^{th} quintile of $R^2_{n,t}$ and 3^{rd} frequency tercile) with the returns of pension funds in the double sorted portfolio 1/3 (1^{st} quintile of $R^2_{n,t}$ and 3^{rd} frequency tercile). Namely, the table compares the returns of pension funds that are more often categorized as follower pension funds over time with the results of pension funds that more often categorized as non-follower pension funds. The table also reports the risk-adjusted returns based on the CAPM and the Fama and French's (2012) global size, value, and momentum factors as well as North-American size and value factors. The risk-adjusted returns are the intercept from a time-series regression of the double-sorted portfolios' excess returns over the U.S. one month T-bill rate on the risk factors. The CAPM market return is given by the monthly total return on the MSCI All Country World Index. For the time-series regression on North-American factors the market risk premium is the return on the region's value-weighted market portfolio minus the U.S. one month T-bill rate. All factors are converted into euro returns. The t-statistics are in parentheses and are computed using Newey-West standard errors with three lags. The * indicates statistical significance at the 10% level, ** at the % 5 percent, and *** at the1% level.

Double sorting	(1/3)	(5/3)	(5/3)-(1/3)
Avg. $R^2_{n,t}$	0.0002	0.1954	0.1952
	Return month t+1 (%)		
Average	1.1651***	0.9933***	-0.1719*
	(3.94)	(3.23)	(-1.88)
CAPM α_{MSCI}	0.0911	-0.1160	-0.2071**
	(1.37)	(-1.03)	(-2.18)
G4F α	0.1557	-0.0298	-0.1855*
	(1.42)	(-0.19)	(-1.86)
3F NA α	-0.1035	-0.2830	-0.1795*
	(-0.55)	(-1.13)	(-1.76)
	Return month t+3 (%)		
Average	3.6403***	3.1165***	-0.5238***
	(4.75)	(3.94)	(-2.80)
CAPM α_{MSCI}	0.4922***	-0.1295	-0.6217***
	(2.66)	(-0.51)	(-3.41)
G4F α	0.4056	-0.1512	-0.5568***
	(1.52)	(-0.45)	(-2.85)
3F NA α	-0.5227	-1.0201	-0.4974**
	(-0.92)	(-1.50)	(-2.24)