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

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**ABSTRACT**

I use proprietary data on equity holdings to show that Dutch pension funds herd in individual securities. I introduce a pension fund-level measure of herding that identifies the extent to which a pension fund follows other pension funds into and out of the same securities over time. I show that pension funds that herd underperform pension funds that do not herd by 1.32% on an annual basis that indicates herding has a negative impact on performance. Small pension funds and pension funds that trade less frequently are more likely to herd. These pension funds herd consistently over time, hence they appear to make this decision strategically out of reputational concerns.

**Key words**: herding, investment skills, pension funds, performance, security selection

**JEL classification**: G11, G23.

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Public equity is one of the main asset classes within the portfolio of any pension fund. Constructing an equity portfolio entails a number of decisions by a pension fund's board of trustees and asset managers that are employed to implement the investment policy. The first decision is the allocation of the equity portfolio across different geographic regions. The second decision is the benchmark selection or the identification of their universe of eligible equity investments (Broeders and De Haan (2020)). The third decision is to either follow an active or a passive strategy that is defined by how closely a portfolio tracks its benchmark. The fourth and final decision is the security selection or choice of the individual securities to invest in that meet a pension fund's requirements. All these decisions are prone to herding (Lakonishok et al. (1992)).

In this paper, I examine herding at the security selection level, that is, investors following each other into and out of the same securities over time. Investors may herd because they infer information from each other's trades (Banerjee (1992)), because of common signals (Bauer et al. (2020)), because of homogeneous preferences (Falkenstein (1996), Bennett et al. (2003)), or because they are concerned about underperforming their peers (Scharfstein and Stein (1990)). Herding is a sequential behavior: it starts with an investor that trades a particular security. In the subsequent period, another investor trades the same security, in the same direction, by either observing or inferring the trade of the first investor. Less skilled or less informed investors may decide to herd on the trades of first movers. Investors with better skills may instead decide to trade against other investors, that is, anti-herd to exploit their advantage (Jiang and Verardo (2018)).

I study herding in the equity portfolios of Dutch occupational pension funds, and I investigate whether herding influences their performance.[1] I first rely on the herding measure developed by Sias (2004) to test herding among all pension funds. Next, I introduce a pension fund-level measure of herding to test the effect of herding on performance. This measure identifies the extent to which an individual pension fund follows other pension funds. I define a "follower" as a pension fund whose future trades are largely explained by the aggregate trades of other pension funds today.

I show significant herding among pension funds, as the current aggregate demand for securities is positively correlated with the past aggregate demand for the same securities. Next, I show that pension funds that herd ("followers") underperform pension funds that do not herd by 1.32% on

[1] The literature on herding has mainly focused on mutual funds. A number of studies investigate the effect 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).

an annual basis. I obtain similar results if I account for pension funds' exposures to global factors such as the market, size, value, and momentum factors. Therefore, the underperformance is not driven by differences in risk exposures. In a multivariate regression, herding negatively predicts four-factor alphas after controlling for pension fund characteristics. Hence, herding negatively affects performance.

The underperformance of followers may be explained by their inability to acquire timely information. Investors that acquire information first, either by chance or by having better skills, can exploit this information to their advantage (Hirshleifer et al. (1994)). Conversely, investors unable to acquire timely information may decide to follow those that do. My results indicate that herding is related to scale, as small pension funds are more likely to be followers. These pension funds may not be able to select the highest skilled asset managers. Followers also have a lower turnover that indicates they might be unable to trade frequently. Furthermore, followers trade a smaller set of securities that results in a less diversified portfolio.

If herding does not lead to greater performance, why do some pension funds follow others? The rich theoretical foundation for institutional herding distinguishes between information cascades and reputation herding.[2] First, models of information cascades posit that investors herd by inferring information from each other (Bikhchandani et al. (1992)). In line with these cascades, I find that pension fund herding is stronger in equity markets with lower analyst coverage, such as small capitalization securities and emerging markets, and thus where learning from other investors can be valuable (Wermers (1999)). Moreover, small pension funds are more likely to be followers, as they generally have less resources to do investment research. Second, the fear of underperforming their peers 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 concern, herding appears to be a strategic decision because pension funds consistently herd over time. Pension funds that are categorized as followers in one month tend to also be a follower in subsequent months. Moreover, the fact that small pension funds herd more is also in line with reputation herding. Small pension funds have generally less in-house expertise and therefore tend to delegate more decisions to their asset management firms. Asset management firms have the incentive to retain clients and herding can be a strategy to reduce their

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

responsibility in the event of poor performance. Moreover, it is more efficient for asset management firms to execute the same security selection for different clients.

I perform a number of tests to show that herding does not arise from reasons other than pension funds 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 decide to invest the periodic contributions in the same securities to keep their portfolio weights constant. Therefore, pension funds do not mechanically herd because of correlated cash flows and similar portfolios. Second, I investigate if herding is driven by pension funds' preferences for securities with certain characteristics, which is in line with style-investing (Barberis and Shleifer (2003)). I find that herding in individual securities persists after controlling for lag returns, market capitalization, and the book-to-market ratio.

The loss of returns related to herding has a direct effect on the funding ratio of a pension fund.[3] In the Dutch context, the active participants in a poorly funded pension fund may face an increase in their contribution rate. Furthermore, both the active participants and the retirees may experience a reduction in indexation or even a reduction in accrued pension benefits.[4] Therefore, participants and retirees bear the costs of herding.[5] In other jurisdictions, the costs of herding are borne by the stakeholders that bear the underfunding risk. In the case of UK corporate pension funds this is the firm offering the pension plan and in the case of US public pension funds these are the tax payers.

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 this performance to their size and cost efficiency (Bauer et al. (2010), Dyck and Pomorski (2011), Andonov et al. (2012), and Blake et al. (2013)). I concentrate on security selection to show that the low performance of small pension funds is not only related to the lack of economies of scale, but it is also a consequence of herding. Second, I contribute to the empirical literature on herding. Other papers measure herding at the security level as the correlation among institutional investors' demand for the same securities over

[3]The ratio of the value of assets over the present value of future liabilities.

[4]Indexation is also known as a cost of living adjustment. The Pension Fund Act in the Netherlands prescribes that this indexation can only be awarded in full if the funding ratio is sufficiently high. In the case when the pension is severely underfunded, accrued pension benefits must be reduced to restore funding.

[5]There is an absence of market discipline in occupational pension funds. It is difficult for participants to leave a pension fund in case of poor investment performance. They can only exit their pension fund by changing jobs and transferring accrued pension benefits from one pension fund to another. This "voting with their feet" would furthermore require finding a job at a firm with a better performing pension fund.

time.[6] I introduce a pension fund-level measure of herding that identifies followers. This measure connects herding to pension fund characteristics such as size, turnover, past returns, and flows.[7] Moreover, the findings in this paper show stronger herding compared to earlier evidence of herding among pension funds provided by Lakonishok et al. (1992). Hence, over time pension funds appear to have developed a stronger tendency to herd in their equity investments.

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 pension fund-level measure of herding. Section IV investigates the relation between herding and pension fund return. Section V describes the motivations underlying herding. Section VI addresses alternative explanations for herding. Section VII concludes.

# I. Institutional Setting Data

In this section, I briefly describe the Dutch occupational pension sector. Next, I introduce the institutional ownership data used in this study.

## *A. The institutional setting*

The Dutch pension system consists of the usual three pillars. The first pillar is a state pension available to all citizens in the form of a basic income starting at the statutory age of retirement. The second pillar is the semi-mandatory occupational pensions that are administered by a pension fund or by an insurance company. The Dutch law distinguishes three types of occupational pension funds: industry-wide pension funds, corporate pension funds, and pension funds for independent professionals. Pension funds are legally and financially independent from the companies. The third pillar consists of individual voluntary pensions.[8]

[6] This literature has its origin in Lakonishok et al. (1992) who developed 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), and 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.

[7] Flows in a pension funds capture the difference between contributions coming in and benefits being paid out.

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

The Dutch occupational pension funds manage a total of 1,323 billion euros that corresponded to 170% of the Dutch GDP as of December 2018. The dominant pension contract is a hybrid of defined benefit (DB) and defined contribution (DC). 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 accrued benefits partially cut in case of severe underfunding of the pension fund. The employer automatically enrolls its employees in the pension fund, and they cannot express individual preferences on the contribution rate or asset allocation, both of which are decided by pension fund's trustees within the boundary of the law.[9] The trustees employ internal or external asset managers to perform the security selection within different asset classes. Participants cannot leave the pension fund in which they are enrolled unless they switch employers.

Occupational pension funds are particularly suited to investigate herding for a number of reasons. First, pension funds are subject to solvency regulations which can influence their demand for assets with specific characteristics (Greenwood and Vissing-Jorgensen (2018)).[10] Second, pension funds may respond with similar investment strategies to the long-lasting decline in market interest rates that affect the present discounted 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 pension funds. Their investment performance is disclosed publicly; this performance faces the scrutiny of pension funds' stakeholders and the board of trustees who can decide to replace the asset manager in case of poor performance.[11] Asset management firms

[9]Employers and employees (social partners) negotiate on the features of the pension scheme, e.g. on the accrual rate and indexation target. Next the pension fund determines the contribution that are needed to finance new accruals within the boundaries of the law. If social partners are not willing to pay that contribution, this will imply a lower accrual rate.

[10]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 have shown the effect 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 in asset allocations across pension funds in the Netherlands, US, and Canada.

[11]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, then the pension fund's stakeholders can contest the mandatory nature of the pension fund. For example, the collective labor agreement in some industries establishes that all companies within the industry must join the industry-wide pension fund set up by the industry

have the incentive to retain their clients and herding can be a strategy to reduce their responsibility in the event of poor performance Scharfstein and Stein (1990). Fifth, the geographical proximity, the social network of pension fund trustees, and common advisors facilitate the transfer of investment beliefs across pension funds (Bauer et al. (2020)).

### B. *Security holding data*

The data for this study are the detailed public equity holdings of Dutch institutional investors who operate in the pension sector. The data are proprietary and provided by the prudential supervisor of pension funds, De Nederlandsche Bank (DNB). The sample consists of the public equity holdings of 44 pension funds and 18 pension asset management firms and correspond to 98% of the value of all public equity investments for a total of 21,230 unique securities in the Dutch pension fund industry. DNB requires the largest 44 pension funds, that are systematically important, to report monthly their holdings of individual securities. Smaller pension funds are not required to directly report their holdings. However, DNB requires Dutch asset management firms 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, one asset management firm 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 in which pension funds hold more than 80% of the assets every month. Second, I aggregate the holdings of all investment funds managed by the same asset management firm. After this procedure, I am left with the security holdings of 18 asset management firms that manage pension assets. These holdings can be merged with those directly reported by 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 herding originates from the asset management firm of each pension fund that is the actual decision maker when it comes to security selection.

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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.

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 at the end of each month as well as the value of the securities bought and sold throughout the month.[12] The holding data are merged with security-level information such as price, total returns, market capitalization, and the book-to-market ratio from Factset. The sample comprises international securities. Since the data on holdings are in euros, the security-level information is converted to euros. The dataset covers the period from January 2009 to December 2018 for a total of 120 months.

Table I presents the summary statistics of the holdings data. The average equity portfolio of the pension funds in the sample is 5.7 billion, and the median is 1.1 billion. The standard deviation is high because of a few very large pension funds. 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 different securities held is 1,464, and the median is 1,179. Pension funds report an average exposure to European equities of 43%. North American (US and Canada) securities account for 32% of the portfolio, Asian and Pacific 12%, and emerging markets account for 13%.[13] Over the sample period, the average monthly gross portfolio return is 1.1%. Pension fund returns are computed using the Dietz (1966) method:

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

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 of security $j$ traded by pension fund $n$ during month $t$: total purchases minus total sells. $EX_{n,j,t}$ is the change in the 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, I assume that transactions are on average executed halfway through the month. $R_{n,j,t}$ is therefore the return on the position in each security. Pension funds' total returns are computed as the weighted average of the returns on each position, where weights are

[12] I use the split-adjusted number of securities for all the calculations in the paper.

[13] 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.

the share of each security in the pension fund's portfolio.

Pension funds report an average turnover ratio of 2% (median 0.6%) and an average flow of 0.04% (median -0.02%). The pension fund turnover ratio is the absolute value of the ratio between net purchases at the end of a month and the portfolio value at the beginning of the month (see, e.g., Brennan and Cao (1997)). In line with Sialm et al. (2015), pension fund flows are defined as the incremental value of a pension fund's portfolio at the end of a month that is not due to portfolio returns over that month. Pension fund flows are driven by cash flows from contributions coming in and benefit payments going out. Moreover, flows can capture the heterogeneity in pension funds' strategic asset allocations. For example, if a pension fund's board of trustees decides to increase the strategic allocation to fixed-income securities, this increase will translate into an outflow from the equity portfolio.

# II. Pension funds' herding

In this section, I show that Dutch pension funds, as a group, follow each other into and out of the same securities over time by 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 if the number of securities held at the end of the month is greater than the number of securities held at the beginning. A pension fund is a seller if the number of securities held at the end of the month is smaller than the number of securities held at the beginning. A pension fund is classified as a trader, if it is either a buyer or a seller. If the number of securities 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 securities within a month is classified as neither a buyer nor a seller. For each month, I calculate the raw fraction of pension funds that buy security $j$ during month $t$:

$$Raw\Delta_{j,t} = \frac{No.\ of\ Pension\ funds\ buying_{j,t}}{No.\ of\ Pension\ funds\ buying_{j,t} + No.\ of\ Pension\ funds\ selling_{j,t}} \tag{2}$$

I exclude the initiation and liquidation of a position. Namely, I exclude securities that are purchased for the first time by a pension fund and securities that disappear from the pension fund's portfolio in a given month.

Table II presents the average number of securities with at least 1, 3, 5, or 10 pension funds trading it 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 that are traded by at least 1 pension fund each month, 2,246 securities traded by at least 3, 1,397 securities traded by at least 5, and 428 securities traded by at least 10 pension funds. These numbers are quite stable over time as shown by the following columns. The average number of securities each year is 9,663 meaning that roughly half of the securities in the sample are not traded every month. However, there is a number of securities that are often traded by several pension funds.

### *B. Aggregate herding measure*

As several pension funds trade a lot the same securities, it is important to establish if herding is driving these trades. To measure pension fund herding in the same securities, I first standardize the raw fraction of pension funds that buy (standardized pension fund demand) in the following way:

$$\Delta_{j,t} = \frac{Raw\Delta_{j,t} - \overline{Raw\Delta_t}}{\sigma(Raw\Delta_{j,t})} \tag{3}$$

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:

$$\Delta_{j,t} = \beta_t \Delta_{j,t-1} + \epsilon_{j,t}. \tag{4}$$

Because the data are standardized and there is only one independent variable, the coefficients for each cross-sectional regression in Equation (4) can be interpreted as the correlation between the standardized demand for security $j$ ($\Delta_{j,t}$) and the standardized lag demand for security $j$ ($\Delta_{j,t-1}$).[14] A positive correlation between the pension fund demand and the pension fund lag demand can occur because pension funds follow themselves 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 pension funds that are buyers can be written as the sum of a series of dummy variables for each pension fund that equal one if the pension fund is a buyer and zero if it is a seller divided by the number of pension funds that are either buyers or sellers. As a result, the $\beta$ coefficient in Equation (4) can be rewritten as:[15]

$$
\begin{aligned}
\beta_t = \rho(\Delta_{j,t}, \Delta_{j,t-1}) = & \left[\frac{1}{(J-1)\sigma(Raw\Delta_{j,t})\sigma(Raw\Delta_{j,t-1})}\right] \\
& \times \sum_{j=1}^{J}\left[\sum_{n=1}^{N_{j,t}} \frac{(d_{n,j,t}-\overline{Raw\Delta_t})(d_{n,j,t-1}-\overline{Raw\Delta_{t-1}})}{N_{j,t}N_{j,t-1}}\right] \\
& + \left[\frac{1}{(J-1)\sigma(Raw\Delta_{j,t})\sigma(Raw\Delta_{j,t-1})}\right] \\
& \times \sum_{j=1}^{J}\left[\sum_{n=1}^{N_{j,t}} \sum_{m=1,m\neq n}^{N_{j,t-1}} \frac{(d_{n,j,t}-\overline{Raw\Delta_t})(d_{m,j,t-1}-\overline{Raw\Delta_{t-1}})}{N_{j,t}N_{j,t-1}}\right]
\end{aligned}
\tag{5}
$$

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 $t-1$, $d_{n,j,t-1}$ 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 (5) is the portion of the correlation that results from pension funds following themselves into and out of the same securities over subsequent months.

[14] The standardization of the data is necessary to interpret the coefficient in Equation (4) as a correlation. Then, I can split the correlation coefficient into two terms as described in Equation (5). Moreover, the standardization makes possible the aggregation of the coefficients over time to directly compare them. Each regression coefficient depends on the scale of the data, if the pension funds' demand was not standardized, then the comparison of different cross-sectional regression coefficients would be inappropriate.

[15] For the proof see Sias (2004).

The second term in the right-hand side of Equation (5) 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 if pension fund $m$ sells (buys) security $j$ in month $t-1$. In that case, pension funds display anti-herding behavior. If the demand of pension fund $n$ is not correlated with the lag demand of pension fund $m$, then the second term is zero, that is, pension funds do not herd.

I find significant herding among pension funds as a group. Table III presents the time-series average coefficients from 119 cross-sectional regressions described by Equation (4) and the coefficient decomposition described by Equation (5). Panels A, B, and C show strong statistical evidence that pension funds follow themselves and each other into and out of the same securities. For securities with at least 3 trading pension 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.[16] 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, that is, spreading their trades over subsequent months. The results for the sample of securities with at least 5 and 10 trading funds also show that pension funds herd and spread their trades over subsequent months.[17],[18] The remainder of the analysis will be carried out on the sample of securities with at least three traders. This choice is motivated by the fact that on the one hand, I am interested in identifying the determinants of herding and therefore a minimum number of traders in each security is necessary to study such a behavior. On the other hand, I am

[16]The standardization has little effect on the regression coefficient in Equation (4). Using the raw data instead of the standardized data, the slope coefficient is 0.1806 (t-statistic = 30.32) when limiting the sample to securities in more than 3 trading pension funds. The slope coefficient is 0.1830 (t-statistic = 26.80) when limiting the sample to securities in more than 5 trading pension funds, and 0.1990 (t-statistic = 20.10) when limiting the sample to securities in more than 10 trading pension funds.

[17]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 trading reduces the portion of the correlation due to herding. Details are available on request.

[18]In unreported results, I show that the results are unchanged, if I estimate Equation (4) and Equation (5) by excluding the securities 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)). Details are available on request.

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. Pension fund-level measure of herding

Theoretical models of herding depict 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 because they measure herding at the security level. Hence, they capture the extent to which investors, as a group, buy or sell the same securities over time. However, herding occurs after an agent provides a first piece of information through an action to another, which action in turn is replicated. To better capture this sequential nature, and to understand the drivers of herding, I develop a measure that identifies the extent to which a pension fund follows other pension funds into and out of the same securities over time. I define a "follower" as a pension fund whose future trades are largely explained by the aggregate trades of other pension funds today. In the mutual fund literature, a similar herding measure was developed by Jiang and Verardo (2018).

To identify followers, I estimate the contribution of all other pension funds' current 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 for security $j$ of all other pension funds except for pension fund $n$ itself:

$$D_{n,j,t} = \alpha_{j,t} + \beta_{n,t} D^{n}_{N,j,t-1} + \epsilon_{j,t} \tag{6}$$

where $D_{n,j,t}$ is the change in the number of securities $j$ in the portfolio of pension fund $n$ during month $t$ that are scaled by the number of securities held at the end of month $t-1$: $D_{n,j,t} = (No.Shares_{n,j,t} - No.Shares_{n,j,t-1})/No.Shares_{n,j,t-1}$. $D^{n}_{N,j,t-1}$ is the change in the number of securities $j$ in the portfolio of all pension funds other than pension fund $n$ during month $t-1$:

$$D^n_{N,j,t-1} = \frac{(No.Shares_{N,j,t-1} - No.Shares_{n,j,t-1}) - (No.Shares_{N,j,t-2} - No.Shares_{n,j,t-2})}{(No.Shares_{N,j,t-2} - No.Shares_{n,j,t-2})} \quad (7)$$

where $No.Shares_{N,j,t-1}$ is the total number of securities $j$ in the portfolio of all pension funds in month $t-1$. Therefore, Equation (7) is the change in the aggregate ownership of pension funds, except $n$, of security $j$ during month $t-1$.

I estimate Equation (6) for each pension fund $n$ for each month $t$. The regression $R^2$ of Equation (6), $R^2_{n,t}$, is the fraction of variation in pension fund $n$'s demand at time $t$ that is explained by the demand of all other pension funds. This is a measure 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, after having measured herding for each pension fund, I examine the relation between herding and gross portfolio returns to investigate if follower pension funds can profit from herding. I begin with a univariate portfolio test to link herding to portfolio returns. Then, I study if the relation between herding and performance persists over time. Next, I estimate predictive regressions of pension fund performance that control for multiple pension fund characteristics to examine if herding can predict future performance.

### *A. Follower pension funds' portfolio performance*

Do follower pension funds profit from herding? To address this question, I identify the pension funds that herd the most, and I compare their performance with the performance of pension funds that do not herd. Panel A of Table IV presents the summary statistics of the herding measure: $R^2_{n,t}$. These statistics are computed cross-sectionally each month and then averaged over 119 months. The mean of $R^2_{n,t}$ is 4% which indicates that on average the lag demand of all other pension funds explains 4% of the variation in each pension fund's demand. The standard deviation is 12.69% that indicates high variability in the herding measure. In fact, the 5th percentile is 0% that indicates no herding, while the 95th percentile is 18.27% that indicates strong herding.

In panel B, I use a portfolio-based analysis to examine the difference in performance between follower and non-follower pension funds. At the end of each month, I sort pension funds into five portfolios based on the estimated $R^2_{n,t}$. Next, I compute equally weighted returns for each quintile portfolio over the next month and the next quarter. Figure 1 shows a graphical representation of the portfolio formation methodology. Then, I estimate the risk-adjusted excess returns of these portfolios as intercepts from time-series regressions on the capital asset pricing model (CAPM) and the global three-factor model of Fama and French (2012) that is augmented with the global momentum factor.[19] To account for the fact that pension funds hold a sizable portion of their equity portfolio in North American securities, 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 US one-month T-bill rate in all specifications.

In the top row of Panel B, I summarize the average $R^2_{n,t}$ in each quintile. Pension funds in the top quintile are followers (column 5). Non-followers 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 is equivalent to a return differential of 1.32% per year.[20] 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, the Global 4-factor model, and the North American 3-factor model are: -0.12%, -0.10%, and -0.10%, and are statistically significant.Three months after portfolio formation the quintile portfolio of follower pension funds underperforms the quintile portfolio of non-follower pension funds by 0.22%. However, the difference disappears after correcting for risk factors. This disappearance indicates that over a quarter, pension funds that herd more are exposed to the same risk factors as pension funds that herd less.

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

[20] Note that the estimated underperformance of 1.32% per year has large standard errors. The hypothesis that the underperformance is null can only be rejected at conventional significance levels. The large standard errors are due to the small cross-section (62 institutions). The quintile analysis presented in Table IV further splits the sample, and as a result the average monthly return computed in each quintile comes from no more than 12 pension funds.

In subsection A of the appendix, I replicate the quintile portfolio analysis across different security characteristics. 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 compute quintile portfolios based on $R^2_{n,t}$ in small capitalization securities as opposed to large capitalization securities, and in emerging market securities as opposed to developed market securities. Table XI shows that pension funds herd more in small capitalization securities than large ones, as the average $R^2_{n,t}$ in each quintile is larger when limiting the sample to small securities (Panel A) than when limiting the sample to large securities (Panel B). Follower pension funds slightly underperform non-follower pension funds in both small and large capitalization securities. However, the difference is not statistically significant.[21] Table XII shows that pension funds herd more in emerging markets than in developed markets, as the average $R^2_{n,t}$ in each quintile is larger in the sample of emerging-market securities (Panel B) than in the sample of developed-country securities (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.

## B. *Herding over time*

The herding measure $R^2_{n,t}$ is relatively stable over time: pension funds with a high $R^2_{n,t}$ measure in one month tend to have a high $R^2_{n,t}$ measure the subsequent month too, and vice versa for pension funds with a lower $R^2_{n,t}$ measure. Therefore, pension funds that are categorized as followers in one month are also categorized as followers in the subsequent months. To show this status, I sort pension funds into five quintiles based on their tendency to follow others. 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. For example, within quintile 5 based on $R^2_{n,t}$ (the quintile of follower pension funds), I sort pension funds into three terciles where tercile 3 is the tercile of pension funds that are more often followers. Similarly within quintile 1 of $R^2_{n,t}$, tercile 3 is the tercile of pension funds that are more often non-followers. This procedure generates 15 double-sorted portfolios of pension funds (15×3). There are seven pension funds that are often

[21] This analysis focuses on a few securities, specifically the first and fifth size quintile of securities in each pension fund's portfolio. Large return differentials in a few securities can lead to large standard errors in the t-tests on the average returns.

categorized as followers, and each of them is categorized as such in 53, 55, 50, 47, 53, 34, and 32 months out of the 119 in the sample period. The pension funds that are often categorized as non-followers are nine and each of them is categorized as such in 41, 52, 35, 33, 37, 34, 43, 58, and 36 out of 119. Figure 2 shows that there is no overlap between these two groups. Each number in the scatter plot refers to a unique pension fund. Followers and non-followers are two distinct groups of pension funds. The same pension fund does not appear as both a follower and non-follower over time. This uniqueness indicates that herding is a strategic decision, and it might be related to pension fund characteristics.

Next, I compute equally weighted returns of the double-sorted portfolio of pension funds. In Table V, 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 followers with the results of pension funds that are more often categorized as non-followers. I also report the risk-adjusted returns of these portfolios as intercepts from the time-series regressions that use the capital asset pricing model (CAPM), the global three-factor model of Fama and French (2012) that is augmented with the global momentum factor, the North American market risk premium, size, and value factors. Pension funds that are more often categorized as followers underperform pension funds that are more often categorized as non-followers by 0.17% on a monthly basis and by 0.52% on a quarterly basis. This result is in line with the findings in Table IV and indicates once again that herding negatively affects 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.

The negative effect on performance is likely due to the fact that by inferring information from others, pension funds might acquire non-timely information. Pension funds that do not herd appear to be the most skilled investors, which is in line with the evidence from mutual funds (Jiang and Verardo (2018)). Non-follower pension funds might be contrarian investors that consistently trade against the crowd, as described by Wei et al. (2015), or might trade a different set of securities from other pension funds. My findings are in line with the latter, as non-follower pension funds hold more different securities in their portfolios. The pension funds that are more often categorized as non-followers over time on average have more than 2,000 different securities in their portfolios, while the sample average has 1,464. This difference indicates that non-followers have a more diversified equity portfolio. In Figure 3, I show graphically that indeed there is a negative relation between the time-series average of the $R^2_{n,t}$ of a pension fund and the number of securities held. Pension funds that herd more hold less securities than those that do not herd.

### *C. Return prediction*

To further explore the relation between returns and herding, I estimate multivariate pooled OLS regressions for the performance of pension funds on herding and other pension fund characteristics. The measure of performance that I use is the monthly global four-factor alpha estimated from the realized gross return of each pension fund in excess of the US 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 VI presents the predictive pooled OLS results. Columns (1) shows a univariate regression of the four-factor gross alphas on the lag measure of herding ($R^2_{n,t}$). Herding negatively predicts future performance. The slope coefficient associated with the past level of $R^2_{n,t}$ is negative and significant at the 1% level. A 1% increase in the past level of $R^2_{n,t}$ is associated with a 0.0023 percentage points lower monthly alpha of a pension fund. After controlling for pension fund characteristics, in column (2), the relation between performance and herding remains significantly negative and almost unchanged in magnitude (coefficient =-0.0020). Hence, high herding predicts lower future risk-adjusted returns. Column (4) shows that after controlling for pension fund characteristics, follower pension funds are associated with a 0.05 percentage points lower next-month alpha. But column (6) indicates that non-followers are associated with a 0.02 percentage points higher next-month alpha. In line with the quintile-portfolio analysis, these results show that herding negatively affects performance.

Table VI also indicates that corporate pension funds show greater performance than pension asset management firms and that low portfolio turnover positively predicts future alpha, which is in line with the results from mutual funds (Carhart (1997)). Moreover, size does not predict better future performance in public equity. However, size is not unrelated to investment skills. In Table XIII of subsection B in the appendix, I show that size positively predicts the next-month alpha if correlated variables such as the type of pension fund and herding are dropped.

# V. Determinants of herding

The results from the previous subsections lead to a natural question: if herding does not lead to greater performance, why do pension funds herd? In this subsection, I investigate the relation between the herding measure and several pension fund characteristics to understand which ones drive pension funds to herd.

To address this question, I begin by estimating pooled OLS regressions of $R^2_{n,t}$ on a number of pension fund characteristics such as the type of institution which is a categorical variable to identify either industry-wide pension funds, corporate pension funds, or pension asset management firms.[22] Other characteristics are size (measured as the natural logarithm of the total equity portfolio), turnover, flow, and past returns. Given that pension funds herd more in some equity markets than others, I investigate the relation between $R^2_{n,t}$ and pension fund characteristics in developed and emerging markets separately as well as in large and small capitalization securities 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 is binary and equals one if a pension fund is classified as a follower; that is, it belongs to the $5^{th}$ quintile of the $R^2_{n,t}$ distribution in a given month. The logit regressions are presented in columns (2), (4), (6), and (8).[23]

In all equity markets, small pension funds display a higher $R^2_{n,t}$ and are more likely to be followers.[24][25] Moreover, pension funds with a lower turnover ratio are also associated with a higher $R^2_{n,t}$ and therefore are more likely to be followers. Thus, the pension funds that herd more are generally small and trade less frequently. These results indicate that herding is related to skills and that small pension funds might not be able to select the more skilled asset managers and in turn decide to herd. On the one hand, this relation can be interpreted as small pension funds trying

[22] 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 typically manage the assets of small pension funds.

[23] I use pooled regressions instead of fixed effect regressions because I am mostly interested in explaining the cross sectional differences in the herding measure. In addition, pension funds characteristics are partly time invariant.

[24] Table XIV in subsection C of the appendix shows that the results are really similar, if I also include the number of securities as additional explanatory variables. The number of securities is dropped from the main analysis because it correlates with portfolio size.

[25] The Dutch occupational pension sector is characterized by a few very large pension funds. Thus, outliers might drive the relation between herding and size. In section VII.D, I study the relation between herding and size by using piecewise-linear segments of size as independent variables replacing log size. In Table XV, I show that within groups of pension funds of similar size, smaller pension funds still herd more.

to learn from other, possibly more skilled, pension funds. On the other hand, the earlier finding of persistent herding over time indicates that it is a strategic decision that might arise from the fear of underperforming peers. Hence, small pension funds might herd on the trades of large and more media-covered pension funds (Goyal and Wahal (2008)) because of reputational concerns. In fact, large pension funds are less likely to herd.Information about large (and generally more media covered) pension funds' investment strategies may also be more easily observable by others. For example, these pension funds may employ several brokers who can spread their order flows across their other clients (Barbon et al. (2019)). Furthermore, small pension funds have generally less in-house expertise and therefore tend to delegate more decisions to their asset managers. Asset management firms have the incentive to retain their clients. Therefore, herding can be a strategy to reduce their responsibility in the event of poor performance.

Herding is not affected by passive investing. I hand collected data on the type of equity mandates from the annual reports of the pension funds in the sample. In each annual report, I searched whether a pension would declare that part or the entirety of their equity portfolio was actively or passively managed. On average 60% of the pension funds declare that they mainly rely on active management in their public equity portfolio. However, the number of pension funds in the sample that rely on active management has decreased significantly over time: from 29 in 2009 to 14 in 2018, see Figure 4. In Table VIII, I reestimate the relation between herding and pension fund characteristics after adding a dummy variable that equals one if a pension fund relies on active management in a given month and zero if it relies on passive management.[26] Herding is not affected by the decision of pension funds to rely on active or passive management. Moreover, the coefficients for the other variables are basically unchanged compared to those in Table VII.

## VI. Alternative explanations for herding

The correlation between the fraction of pension funds that buy or sell the same securities this month and the fraction of pension funds that buy or sell the same securities last month might arise mechanically for reasons other than pension funds following themselves or each other into and out of the same securities over subsequent months. For example, pension funds might display

[26] This information is only available on a yearly basis. Therefore, the variable is kept constant for each month in a given year. Changes always occur in January.

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, the cross-sectional and time-series correlations in their net flows could result in correlated trades. This type of herding is defined as "habit investing".[27] Habit investing may arise because of three mechanical reasons. First, if pension funds have similar portfolios because they hold the same securities; second, if pension funds' cash inflows are positively correlated, that is, contributions are paid in the same period or are exposed to common shocks; third, if pension funds invest their incoming contributions proportionally in existing portfolios, then pension funds will mechanically follow each other into the same securities over subsequent periods.

To investigate if habit investing drives herding, I examine the correlation between the fraction of pension funds that increase the return-adjusted portfolio weights over subsequent months, which is in line with Sias (2004). If a pension fund's objective is to maintain a similar portfolio over time when new contributions are flowing in, it would buy securities in proportion to its current holdings. Therefore, portfolio weights would not change and consequently the portfolio weights of different pension funds would be independent over subsequent periods. 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 would 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 during 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 $t$; that is, the price at the end of month $t$ times the number of securities held. Pension fund $n$ is defined as increasing its return-adjusted portfolio weight if its month-end portfolio weight ($w^{adj}_{n,j,t}$) is greater than its return-adjusted portfolio weight

[27]Habit investing also occurs if pension funds follow passive strategies that track the same index. In this case, contributions are reinvested proportionally in all securities to mimic the weights of each security in the index. However, even if pension funds passively track 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 effects as earlier trades have influenced the current prices

at the beginning of the month ($w^{adj}_{n,j,t-1}$). Hence, a pension fund is a buyer if:

$$w^{adj}_{n,j,t} > w^{adj}_{n,j,t-1} \equiv \frac{V_{n,j,t}}{\sum_{j=1}^{J} V_{n,j,t}} > \frac{V_{n,j,t-1}(1+r_{j,t})}{\sum_{j=1}^{J} V_{n,j,t-1}(1+r_{j,t})} \tag{8}$$

where $r_{j,t}$ is the return of security $j$ in month $t$.[28] 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 portfolio weight at the beginning of month ($w^{adj}_{n,j,t-1}$). If $w^{adj}_{n,j,t}$ equals $w^{adj}_{n,j,t-1}$, then 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:

$$Raw\Delta^{w}_{j,t} = \frac{No.\ of\ Pension\ funds\ increasing\ w^{adj}_{n,j,t}}{No.\ of\ Pension\ funds\ increasing\ w^{adj}_{n,j,t} + No.\ of\ Pension\ funds\ decreasing\ w^{adj}_{n,j,t}} \tag{9}$$

Each month, I standardize $Raw\Delta^{w}_{j,t}$ to have a mean equal to zero and a variance equal to one, as in Equation (3). 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 standardized lag fraction of pension funds that increase their return-adjusted portfolio weights for each month, as in Equation (4). 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 (5). Table IX 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, and with similar magnitude to the coefficients in Table III. Herding is slightly lower that indicates a small portion of it is driven by pension funds mechanically reinvesting their net flows in the same portion as the existing holdings,

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

that is, habit investing. However, the portion of correlation that arises from pension funds that follow each other's return-adjusted portfolio weights is strong in all groups of securities, and this strength confirms the existence of herding.

### *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, high book-to-market ratios, or momentum. For example, pension funds might herd because their demand is positively correlated with the prior month's security returns, if pension funds are momentum traders.[29] To test this conjecture, I add the lag standardized return of the security in Equation (4).[30] Specifically, for each month I regress the standardized fraction of pension funds that buy security $j$ on the lag standardized fraction of pension funds that buy security $j$ and the standardized lag return of $j$:

$$\Delta_{j,t} = \beta_{1,t}\Delta_{j,t-1} + \beta_{2,t} r_{j,t-1} + \epsilon_{j,t} \tag{10}$$

All the variables are standardized in such a way as to have a mean equal to zero and a variance equal to one each month. To account for other styles, I also estimate Equation (10) by replacing the lag standardized return with the lag standardized market capitalization and the lag standardized book-to-market ratio. Moreover, I estimate Equation (10) by adding all three security characteristics. Table X presents the time-series average of the regression coefficients for the samples that include all securities with at least 3, 5, or 10 traders.

The results show that adding the lag standardized return, or other lag standardized security characteristics, to the regression has little effect 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 Table III. The average coefficient associated with the lag standardized return, or other security characteristics, is small compared to the average coefficients associated

[29] 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 have shown 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)).

[30] As described in Section II, the standardization of the independent variables allows to aggregate coefficients over time and to easily compare them.

with the lag standardized fraction of pension funds that buy. Furthermore, the average $R^2$ in all panels of Table X are similar to the average $R^2$ in Table III. Therefore, adding lag returns, or other security 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 5 or 10 traders the average coefficient associated with the lag standardized return is negative that means the pension funds are countercyclical traders rather than momentum traders. To conclude, the herding of pension funds is not driven by past returns, security size, or book-to-market ratio. Even if all three styles are added together in the regression, the results remain unchanged.

## VII. Conclusion

In this paper, I study herding in the equity investments of Dutch occupational pension funds, and I investigate whether that herding influences their performance. I begin my analysis by measuring herding across all pension funds as in Sias (2004); that is, the correlation among the demand of all pension funds for the same securities over time. Then, I introduce a pension fund-level measure of herding that identifies the extent to which a pension fund follows other pension funds. A follower is a pension fund whose future trades are largely explained by the trades of all other pension funds.

I find significant herding among all pension funds. However, pension funds that herd more underperform those that do not herd by 1.32% on an annual basis. This underperformance persists after controlling for different risk-exposure and pension-fund characteristics. Herding is related to scale, as small pension funds are more likely to herd. These pension funds may not be able to select skilled asset managers and in turn decide to herd. In addition, pension funds that trade less frequently also herd more. This herding indicates that pension funds that cannot afford trading strategies involving a lot of trades may decide to herd as well.

Herding is stronger in markets with high information asymmetries like small capitalization and emerging markets. Therefore, small pension funds that generally have less resources to use for research might herd to learn from other pension funds. In fact, the information inferred is not timely, as pension funds that herd underperform pension funds that do not herd by 2.76% on an annual basis in emerging markets. The fact that pension funds herd regardless of whether it leads to better performance indicates that they might do so out of reputational concerns. The fear of underperforming their peers can push pension funds to follow each other. Indeed, herding is a strategic decision because pension funds herd consistently over time.

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**Table I**: **Summary statistics**

This table presents the time-series and cross-sectional mean, median, standard deviation, $5^{th}$, $25^{th}$, $75^{th}$, and $95^{th}$ percentile of the public equity portfolio characteristics of pension funds. The portfolio characteristics are the value of 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); and the turnover ratio and flows. Data are for the January 2008 to December 2018 period.

| | Obs. | Mean | Std. Dev. | p5 | p25 | p50 | p75 | p95 |
|---|---|---|---|---|---|---|---|---|
| Tot. portfolio | 5,736 | 5,772,178 | 20,012,368 | 101,796 | 466,856 | 1,143,676 | 3,204,825 | 16,447,118 |
| 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 |
| No. ISIN bought | 5,736 | 238 | 3668 | 2 | 30 | 89 | 279 | 1,042 |
| No. ISIN sold | 5,736 | 210 | 376 | 0 | 18 | 65 | 215 | 1,003 |
| No. ISIN held | 5,736 | 1,464 | 1,372 | 102 | 340 | 1,178 | 2,053 | 4,162 |
| 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 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 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. These dates are chosen to be able to compare equal time windows.

| | Avg. all periods | Jan. 2009 | Jun. 2011 | Dec. 2013 | Jun. 2016 | Dec. 2018 |
|---|---|---|---|---|---|---|
| Panel A: No. 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 |
| Panel B: No. of securities in the sample | 9,663 | 8,843 | 8,150 | 9,107 | 10,458 | 11,703 |

**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 (2). 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 regressions of the fraction of pension funds that buy on the lag fraction of pension funds that buy, as in Equation (4). 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-statistics 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 (5). The fourth column shows 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 the 10% level, ** at % the 5 percent, and *** at the 1% level.

| | Time-series avg. $\beta$ 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: 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 all other pension funds' demand in predicting pension fund $n$'s demand that is estimated following the steps outlined in Section III. Pension funds with a high $R^2_{n,t}$ are defined as follower pension funds. Panel B presents the performance of quintile portfolios of pension funds 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 estimate the risk-adjusted returns based on the CAPM and the Fama and French (2012) global market size, value, and momentum factors (G4F) as well as North-American market, size and value factors (NA3F) in three separate regressions. The risk-adjusted returns are the intercept from a time-series regression of the quintile portfolios excess returns over the US 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 US 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 the 1% 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 $\alpha_{MSCI}$ | 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 $\alpha$ | 0.1458 | 0.0732 | 0.0416 | 0.0632 | 0.0474 | -0.0985* |
| | (1.27) | (0.59) | (0.35) | (0.49) | (0.38) | (-1.98) |
| NA3F $\alpha$ | -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 $\alpha_{MSCI}$ | 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 $\alpha$ | 0.2720 | 0.3102 | 0.1962 | 0.1660 | 0.2510 | -0.0210 |
| | (1.04) | (1.15) | (0.69) | (0.62) | (0.91) | (-0.22) |
| NA3F $\alpha$ | -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 V**: **Pension fund herding over time and 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, in the table 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 more often categorized as non-follower pension funds. The table also gives the risk-adjusted returns based on the CAPM and Fama and French (2012) global market size, value, and momentum factors (G4F) as well as North-American market, size and value factors (NA3F). The risk-adjusted returns are the intercept from a time-series regression of the double-sorted portfolios' excess returns over the US 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 US 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 the 1% 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 $\alpha_{MSCI}$ | 0.0911 | -0.1160 | -0.2071** |
| | (1.37) | (-1.03) | (-2.18) |
| G4F $\alpha$ | 0.1557 | -0.0298 | -0.1855* |
| | (1.42) | (-0.19) | (-1.86) |
| NA3F $\alpha$ | -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 $\alpha_{MSCI}$ | 0.4922*** | -0.1295 | -0.6217*** |
| | (2.66) | (-0.51) | (-3.41) |
| G4F $\alpha$ | 0.4056 | -0.1512 | -0.5568*** |
| | (1.52) | (-0.45) | (-2.85) |
| NA3F $\alpha$ | -0.5227 | -1.0201 | -0.4974** |
| | (-0.92) | (-1.50) | (-2.24) |

**Table VI**: **Herding and pension fund future performance - Predictive regression**
In column (1), the table presents the coefficients from predictive pooled OLSs that estimate the relation between future 4-factor alpha (in %) of pension funds and the herding measure $R_n^2$. In column (3), I include the dummy variable "Follower" that equals one if a pension fund $n$ falls within the $5^{th}$ quintile of $R_n^2$. In column (5), I include the dummy variable "Non-Follower" that equals one if a pension fund $n$ falls within the $1^{st}$ quintile of $R_n^2$. In all specifications, the dependent variable is the monthly global four-factor alpha (in %) that is estimated with rolling-window regressions over the previous three years of the excess return (over the US one-month T-bill rate) of each pension fund on the global market, size, value, and momentum factors from Fama and French (2012). Columns (2), (4), and (6), include control variables for the type of pension fund, prior-month pension fund size, prior-month turnover, and prior-month flow. The types of pension funds are the industry-wide pension fund and corporate pension fund, and 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)<br>G4F $\alpha_t$ | (2)<br>G4F $\alpha_t$ | (3)<br>G4F $\alpha_t$ | (4)<br>G4F $\alpha_t$ | (5)<br>G4F $\alpha_t$ | (6)<br>G4F $\alpha_t$ |
|---|---|---|---|---|---|---|
| $R^2_{n,t-1}$ | -0.0023*** | -0.0020*** | | | | |
| | (-4.56) | (-2.94) | | | | |
| Follower$_{t-1}$ | | | -0.0649*** | -0.0488** | | |
| | | | (-2.85) | (-2.30) | | |
| Non-Follower$_{t-1}$ | | | | | 0.0295** | 0.0186* |
| | | | | | (2.38) | (1.83) |
| Corporate pension fund | | 0.1090** | | 0.1087** | | 0.1076** |
| | | (2.10) | | (2.11) | | (2.04) |
| Industry-wide pension fund | | 0.0809 | | 0.0809 | | 0.0802 |
| | | (1.42) | | (1.43) | | (1.40) |
| Log size$_{t-1}$ | | 0.0139 | | 0.0132 | | 0.0147 |
| | | (1.24) | | (1.18) | | (1.32) |
| Turnover$_{t-1}$ | | -0.0016** | | -0.0017** | | -0.0013* |
| | | (-2.13) | | (-2.30) | | (-1.77) |
| Flow$_{t-1}$ | | -0.0014* | | -0.0014* | | -0.0013* |
| | | (-1.86) | | (-1.86) | | (-1.71) |
| Constant | 0.4337*** | 0.1687 | 0.4350*** | 0.1804 | 0.4173*** | 0.1471 |
| | (18.07) | (1.02) | (18.25) | (1.09) | (16.93) | (0.91) |
| Observations | 3,368 | 3,265 | 3,368 | 3,265 | 3,368 | 3,265 |
| $R^2$ | 0.189 | 0.257 | 0.190 | 0.259 | 0.178 | 0.252 |

**Table VII**: **Determinants of herding**

This table presents columns (1), (3), (5), and (7) the estimated coefficients from pooled OLSs 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. Flow is the pension fund flow in the previous month. $\text{Return}_{t-1}$ is the previous month 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) |
| $\text{Return}_{t-1}$ | 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 | 5,273 | 5,273 | 4,500 | 4,418 | 5,244 | 5,244 | 4,732 | 4,732 |
| $R^2$ | 0.053 | | 0.182 | | 0.104 | | 0.132 | |
| Pseudo $R^2$ | | 0.073 | | 0.166 | | 0.092 | | 0.097 |

**Table VIII**: **Determinants of herding - the effect of active/passive management**
This table presents in columns (1), (3), (5), and (7) the estimated coefficients from pooled OLSs 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. Active is a dummy variable that equals one if a pension fund declares in its annual report that it relies on active management and zero if it relies on passive management. The types of pension funds are the corporate pension fund and the industry-wide pension fund (omitted category). The type "Pension asset management firm" is not included in the regression because these are all active investors. Log size is the natural logarithm of the total equity portfolio of the pension fund. Turnover is the turnover ratio. Flow is the pension fund flow in the previous month. $\text{Return}_{t-1}$ 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) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| | $R^2_{n,t}$ | Follower | $R^2_{n,t}$ | Follower | $R^2_{n,t}$ | Follower | $R^2_{n,t}$ | Follower |
| Active | -0.007 | -0.258 | 0.017 | 0.351 | -0.040 | -0.317 | -0.014 | -0.049 |
| | (-0.65) | (-0.68) | (0.36) | (0.95) | (-1.21) | (-0.72) | (-0.31) | (-0.11) |
| Corporate Pf. | -0.007 | 0.081 | 0.077 | 0.647 | 0.015 | 0.295 | -0.014 | 0.020 |
| | (-0.56) | (0.22) | (1.34) | (1.36) | (0.42) | (0.69) | (-0.26) | (0.04) |
| Log size | -0.014*** | -0.430*** | -0.059*** | -0.694*** | -0.032** | -0.488*** | -0.048*** | -0.413** |
| | (-3.29) | (-3.31) | (-3.69) | (-4.73) | (-2.67) | (-3.52) | (-3.06) | (-2.57) |
| Turnover | -0.175*** | -29.642*** | -0.691*** | -8.049** | -0.347*** | -14.783*** | -0.320** | -4.588* |
| | (-3.43) | (-4.52) | (-2.82) | (-2.52) | (-3.37) | (-3.25) | (-2.68) | (-1.94) |
| Flow | 0.062*** | 2.655 | 0.030 | -1.251 | 0.169*** | -1.275 | 0.124 | -0.012 |
| | (2.82) | (0.70) | (0.20) | (-0.51) | (3.45) | (-0.36) | (1.33) | (-0.01) |
| $\text{Return}_{t-1}$ | 0.072 | -4.998 | -1.565 | -6.438 | -0.620 | -3.081 | 0.322 | 3.255 |
| | (0.21) | (-1.14) | (-1.70) | (-0.62) | (-0.69) | (-0.47) | (0.39) | (0.48) |
| Constant | 0.294*** | 5.608*** | 1.277*** | 8.271*** | 0.577*** | 5.465*** | 0.804*** | 3.322 |
| | (3.88) | (2.99) | (4.84) | (3.93) | (3.27) | (2.65) | (3.62) | (1.48) |
| Observations | 2,948 | 2,948 | 2,399 | 2,357 | 2,904 | 2,904 | 2,708 | 2,690 |
| $R^2$ | 0.084 | | 0.168 | | 0.142 | | 0.109 | |
| Pseudo $R^2$ | | 0.116 | | 0.154 | | 0.131 | | 0.086 |

**Table IX**: **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 this weight (buyer) if it is greater than their return-adjusted beginning-of-month portfolio weight, as described in Equation (8). 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 it to 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 it for each month: Equation (4). 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 (5). The first column presents the time-series average of 119 correlation coefficients. The second and third columns 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 presents 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. $\beta$ 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 X**: **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 (2). 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 (10). Adding these security-level variables allows me to correct for style investing such as: momentum and large or value securities. Standardization (i.e., each month all variables are scaled to have a zero mean and a unit variance) allows me 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 in at least 10 trading funds. The * indicates statistical significance at the 10% level, ** at the % 5 level, and *** at the 1% level.

| | Time-series avg. $\beta$ 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) |

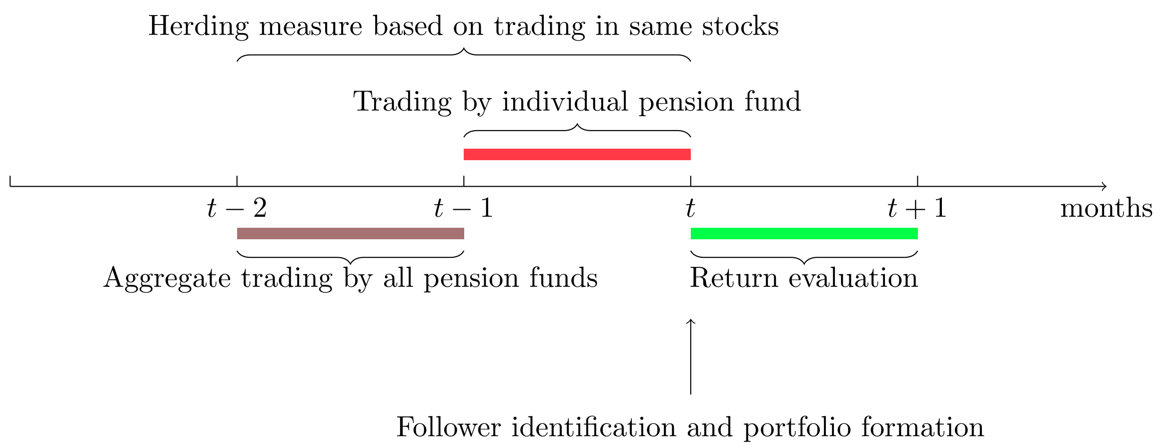


**Figure 1. Portfolio formation methodology**
The figure shows the timeline of the methodologies used to capture herding and then assess the returns of pension funds based on their tendency to herd. First, I measure herding at the end of each month (from $t-1$ to $t$) by relating the trades of a pension with the trades of all other pension funds in the previous month (from $t-2$ to $t-1$). Second, I form portfolios based on the herding measure $R^2_{n,t}$. Third, I assess the next-month returns of the pension fund portfolios that are formed based on quintiles of $R^2_{n,t}$ at the end of month $t$.

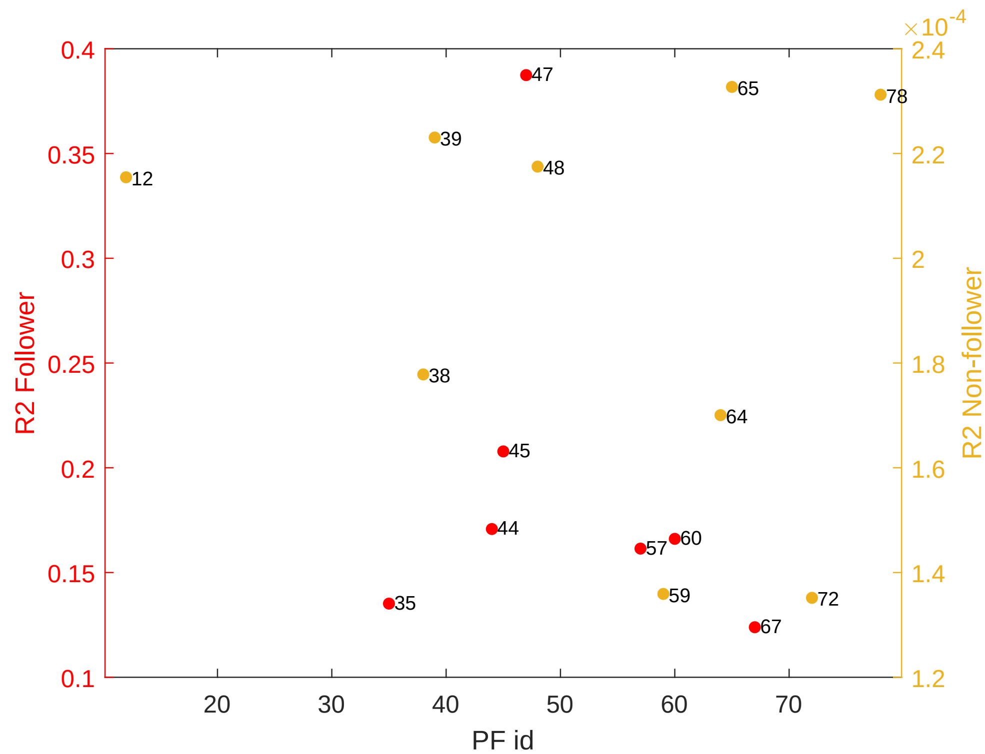


**Figure 2. Followers and non-followers over time**
The figure shows the pension funds that are more often categorized as either followers (red dots) or non-followers (yellow dots). The pension funds are uniquely identified with numbers that are plotted on the X axis. At the end of each month, I sort 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 $R^2_{n,t}$. Pension funds that are more often categorized as followers are those in tercile 3 of frequency within quintile 5 of $R^2_{n,t}$. Similarly, Pension funds that are more often categorized as non-followers are those in tercile 3 of frequency within quintile 1 of $R^2_{n,t}$. The Y axis on the left shows the range of $R^2_{n,t}$ for followers. The Y axis on the right shows the range of $R^2_{n,t}$ for non-followers.

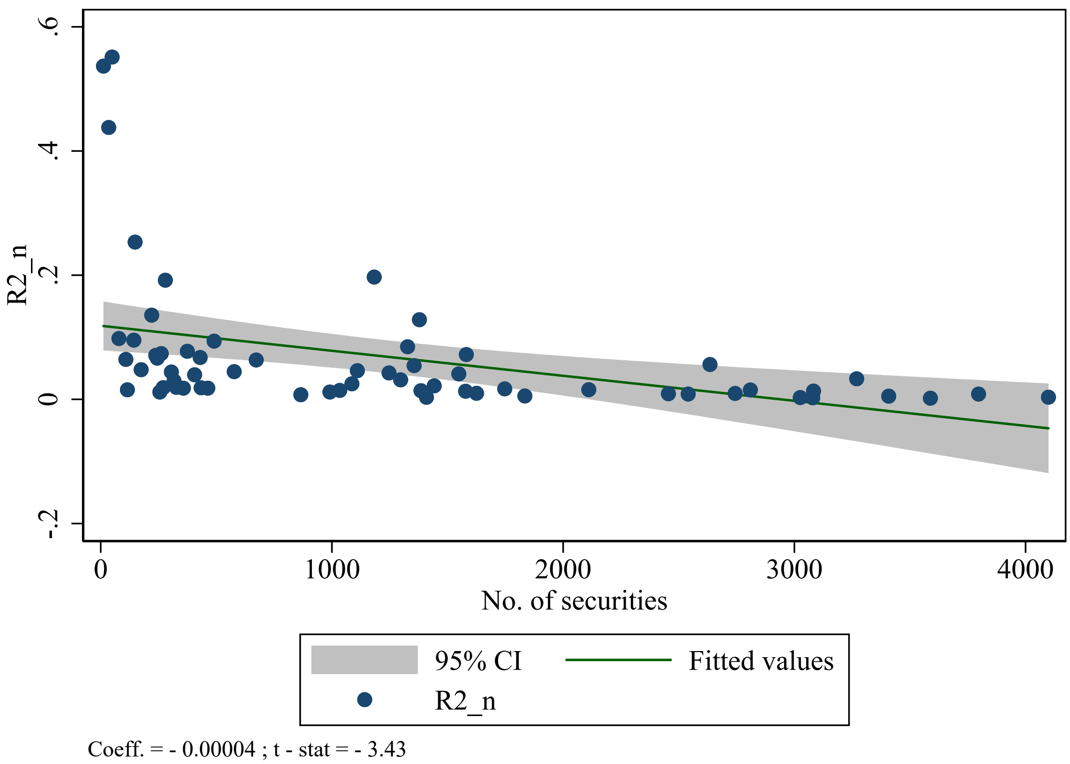


**Figure 3. Relation between herding and number of securities held over time**
The figure shows the relation, together with the regression line, between the time-series average of the herding measure $R^2_{n,t}$ and the number of securities held by each pension fund $n$. The gray-shaded area represents the 95% confidence interval.

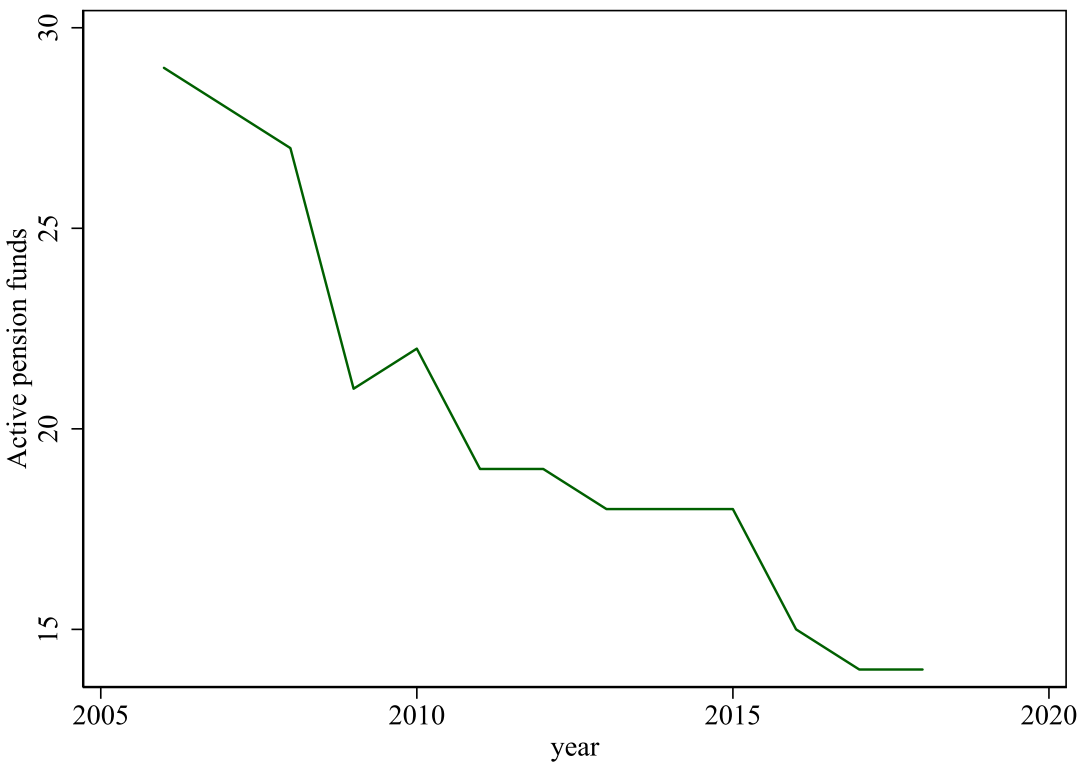


**Figure 4. Number of pension funds relying on active management**
The figure shows the number of pension funds that report in their annual report that part or the entirety of their public equity portfolio is actively managed.

# Appendix

## *A. Returns of followers in different markets*

In this subsection, I examine the difference in performances between follower and non-follower pension funds by only focusing on small capitalization and large capitalization securities. To perform this analysis, I sort all the securities traded by at least three pension funds in each month into five quintiles based on their beginning-of-month market capitalization. I then estimate Equation (6) 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 XI.

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 markets and emerging markets. To perform this analysis, I estimate Equation (6) separately for developed and emerging markets. 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 XII 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 and relies on the same method used in that section.

**Table XI**: **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 (6) 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 (6). 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 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 estimate the risk-adjusted returns based on the CAPM and the Fama and French (2012) global market, size, value, and momentum factors (G4F) as well as North-American market, size and value factors (NA3F) in three separate regressions. The risk-adjusted returns are the intercept from a time-series regression of the quintile portfolios excess returns over the US 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 the 1% level.

| | Panel A: Follower pension funds and portfolio performance - small securities | | | | | |
|---|---|---|---|---|---|---|
| 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 $\alpha$ | -0.0222 | -0.0162 | -0.0195 | -0.0311 | -0.0210 | 0.0012 |
| | (-0.22) | (-0.16) | (-0.19) | (-0.30) | (-0.20) | (0.15) |
| NA3F $\alpha$ | -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 securities | | | | | |
| 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 $\alpha_{MSCI}$ | -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 $\alpha$ | 0.0443 | 0.0562 | 0.0713 | 0.0499 | 0.0251 | -0.0192 |
| | (0.43) | (0.58) | (0.74) | (0.55) | (0.24) | (-0.39) |
| NA3F $\alpha$ | -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 XII**: **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 (6) 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 (6). 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 are 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 estimate the risk-adjusted returns based on the CAPM and the Fama and French (2012) global market, size, value, and momentum factors (G4F) as well as North-American market, size and value factors (NA3F) in three separate regressions. The risk-adjusted returns are the intercept from a time-series regression of the quintile portfolios excess returns over the US 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 market securities. The CAMP alphas for emerging market 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 $\alpha_{MSCI}$ | -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 $\alpha$ | 0.1086 | 0.0684 | 0.0174 | 0.0458 | 0.0200 | -0.0886 |
| | (1.04) | (0.64) | (0.15) | (0.40) | (0.17) | (-1.65) |
| NA3F $\alpha$ | -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 $\alpha$ | 0.0476 | 0.0135 | -0.0247 | -0.0230 | -0.0031 | -0.0507 |
| | (0.42) | (0.11) | (-0.21) | (-0.22) | (-0.03) | (-1.06) |
| NA3F $\alpha$ | -0.1731 | -0.2093 | -0.2513 | -0.2372 | -0.2145 | -0.0414 |
| | (-1.06) | (-1.28) | (-1.54) | (-1.59) | (-1.47) | (-0.76) |

## B. *Predictive regression of pension funds' alpha*

In this appendix, I study the relation between size and a pension fund's future performance by replicating Table VI and excluding the type of pension fund and herding that are variables correlated with pension fund size.

**Table XIII**: **Predictive regression of pension funds' alpha**
The table presents the coefficients from a predictive pooled OLS that estimates the relation between the future 4-factor alpha (in %) of pension funds and pension fund characteristics. The dependent variable is the monthly global four-factor alpha (in %) that is estimated with rolling-window regressions over the previous three years of the excess return (over the US one-month T-bill rate) of each pension fund on the global market, size, value, and momentum factors from Fama and French (2012). Control variables are the previous-month pension fund size, previous-month turnover, and previous-month flow. The model is 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.

| | G4F $\alpha_t$ |
|---|---|
| Log size$t-1$ | 0.0193$^{*}$ |
| | (1.85) |
| Turnover$t-1$ | -0.0021$^{**}$ |
| | (-2.47) |
| Flow$t-1$ | -0.0016$^{**}$ |
| | (-2.31) |
| Constant | 0.1598 |
| | (1.01) |
| Observations | 3,265 |
| $R^2$ | 0.199 |

*C. Determinants of herding including the number of securities in the portfolio*

In this subsection, I replicate the results of Table VII by including the number of securities held by each pension fund among the independent variables in the regression.

**Table XIV: Determinants of herding - number of securities held**
The table presents in columns (1), (3), (5), and (7) the estimated coefficients from pooled OLSs of $R_n^2$, 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 $R_n^2$ on pension fund characteristics. The types of pension funds are the industry-wide pension fund and the corporate pension fund, and 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. | 0.005 | 0.270 | 0.094* | 0.896** | 0.061** | 0.698** | -0.017 | 0.089 |
| | (0.27) | (0.86) | (1.76) | (2.07) | (2.59) | (2.16) | (-0.39) | (0.28) |
| Industry-wide Pf. | 0.007 | 0.267 | 0.018 | 0.131 | 0.027 | 0.400 | -0.003 | 0.132 |
| | (0.30) | (0.73) | (0.38) | (0.32) | (1.21) | (1.16) | (-0.08) | (0.45) |
| Log size | -0.008 | -0.222* | -0.062*** | -0.681*** | -0.018** | -0.319** | -0.034** | -0.216 |
| | (-1.47) | (-1.73) | (-3.22) | (-4.83) | (-2.10) | (-2.41) | (-2.31) | (-1.37) |
| No. securities | -0.000* | -0.000** | -0.000* | -0.000 | -0.000* | -0.000** | -0.000*** | -0.001*** |
| | (-1.78) | (-2.50) | (-1.99) | (-1.50) | (-1.90) | (-2.16) | (-5.32) | (-4.38) |
| Turnover | -0.153*** | -18.674*** | -0.328* | -3.927* | -0.251*** | -16.131*** | -0.254*** | -2.605* |
| | (-4.68) | (-4.71) | (-1.75) | (-1.67) | (-4.39) | (-4.80) | (-2.90) | (-1.81) |
| Flow | 0.029 | -0.476 | 0.017 | 0.115 | 0.048 | -2.309 | 0.052 | 1.187* |
| | (1.64) | (-0.19) | (0.19) | (0.16) | (1.58) | (-1.05) | (1.26) | (1.89) |
| Return$_{t-1}$ | 0.321 | 1.613 | -0.435 | 0.365 | -0.109 | -2.199 | -0.122 | 0.651 |
| | (1.26) | (0.51) | (-0.73) | (0.07) | (-0.22) | (-0.55) | (-0.21) | (0.16) |
| Constant | 0.160*** | 1.776 | 1.174*** | 7.351*** | 0.313*** | 3.026** | 0.687*** | 1.988 |
| | (2.69) | (1.17) | (4.90) | (4.36) | (3.09) | (1.97) | (3.66) | (0.99) |
| Observations | 5,273 | 5,273 | 4,500 | 4,418 | 5,244 | 5,244 | 4,732 | 4,732 |
| $R^2$ | 0.059 | | 0.196 | | 0.112 | | 0.166 | |
| Pseudo $R^2$ | | 0.088 | | 0.183 | | 0.102 | | 0.146 |

*D. Determinants of herding including piecewise-linear segments of size*

The Dutch occupational pension sector is characterized by a few very large pension funds. Thus, outliers might drive the relation between herding and size. In this section, I study the relation between herding and size by using piecewise-linear segments of size as independent variables replacing log size in Table VI.

First, size percentiles are defined based on the log of assets under management each month. Second, low, mid and high size percentiles are defined as follows

$$Low.size_t = min(Percentile_{size,t}, 0.2) \tag{11}$$

$$Mid.size_t = min(max(Percentile_{size,t} - 0.2, 0), 0.6) \tag{12}$$

$$Large.size_t = max(Percentile_{size,t} - 0.8, 0) \tag{13}$$

Table XV shows that the coefficients of all size segment are negative, in line with the log size measure. Mid and large pension funds seem to contribute more in capturing the relation between size and pension fund herding. Large pension funds in the quantile of mid and large pension fund herd less than small pension funds in the same quantiles. Within the group of small pension funds, smaller pension funds herd more than larger pension funds only in emerging markets. The same does not hold in developed markets, or when I separate between large and small cap stocks.

**Table XV**: **Determinants of herding with piecewise size segments**
This table presents columns (1), (3), (5), and (7) the estimated coefficients from pooled OLSs of $R_n^2$, 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 $R_n^2$ on pension fund characteristics. 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. | 0.001 | 0.109 | 0.085* | 0.595* | 0.055** | 0.568 | -0.041 | -0.240 |
| | (0.03) | (0.30) | (1.99) | (1.65) | (2.29) | (1.58) | (-0.84) | (-0.68) |
| Industry-wide Pf. | 0.006 | 0.219 | 0.019 | 0.035 | 0.023 | 0.351 | -0.008 | -0.024 |
| | (0.28) | (0.55) | (0.43) | (0.07) | (1.02) | (0.91) | (-0.17) | (-0.06) |
| Small size | -0.240 | -2.828 | -1.737*** | -7.289** | -0.241 | -2.252 | -0.593 | -2.750 |
| | (-1.43) | (-1.26) | (-3.64) | (-2.35) | (-0.76) | (-1.05) | (-1.15) | (-1.02) |
| Mid size | -0.043 | -1.522** | -0.324*** | -2.748** | -0.160*** | -2.253*** | -0.331*** | -2.614*** |
| | (-1.58) | (-2.20) | (-2.92) | (-2.56) | (-3.79) | (-3.57) | (-4.01) | (-3.60) |
| Large size | -0.158* | -8.818*** | -0.183 | -12.503** | -0.023 | -5.398* | -0.374* | -10.797** |
| | (-1.94) | (-2.81) | (-0.61) | (-2.50) | (-0.29) | (-1.95) | (-1.96) | (-2.50) |
| Turnover | -0.157*** | -18.292*** | -0.427** | -3.625 | -0.261*** | -15.715*** | -0.288*** | -2.631** |
| | (-4.77) | (-4.80) | (-2.37) | (-1.64) | (-4.57) | (-4.86) | (-3.50) | (-2.14) |
| flow | 0.027 | -0.571 | -0.001 | 0.058 | 0.050 | -2.170 | 0.050 | 1.043* |
| | (1.42) | (-0.24) | (-0.01) | (0.08) | (1.59) | (-1.05) | (1.14) | (1.81) |
| $\text{Return}_{t-1}$ | 0.308 | 1.239 | -0.357 | -0.199 | -0.104 | -2.284 | -0.167 | 0.073 |
| | (1.21) | (0.37) | (-0.56) | (-0.04) | (-0.21) | (-0.54) | (-0.30) | (0.02) |
| Constant | 0.106*** | -0.319 | 0.720*** | 0.309 | 0.151*** | -0.273 | 0.411*** | -0.051 |
| | (2.95) | (-0.57) | (8.00) | (0.45) | (2.70) | (-0.46) | (4.27) | (-0.08) |
| Observations | 5273 | 5273 | 4500 | 4418 | 5244 | 5244 | 4732 | 4732 |
| $R^2$ | 0.055 | | 0.217 | | 0.109 | | 0.140 | |
| Pseudo $R^2$ | | 0.078 | | 0.162 | | 0.093 | | 0.107 |

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