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The Market for Lemmings: The Herding Behavior of Pension Funds*

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Abstract

Using a unique dataset that covers UK defined-benefit pension fund asset allocations over the past 25 years, we study the investment behavior of pensions funds. The results suggest that pension funds display strong herding behavior, and tend to herd in subgroups, moving in and out of different asset classes following funds of similar size and sponsor type. Moreover, they systemically switch from equities to bonds as their liabilities mature, and mechanically rebalance their portfolios in the short term.

Keywords: Institutional investors; pension funds; herding; portfolio rebalancing.
JEL Classification: G23.

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1 Introduction

> 'Institutions are herding animals. We watch the same indicators and listen to the same prognostications. Like lemmings, we tend to move in the same direction at the same time.'
>
> `Wall Street Journal, October 17, 1989`

At least since the early 1990s, a number of studies have suggested that institutions are more likely to herd than individual investors. A recurrent argument, for example, is that institutional investors know more about each other's trades than do individual investors (Banerjee, 1992; Bikhchandani, Hirshleifer and Welch, 1992) and react to the same exogenous signals (Froot, Scharfstein and Stein, 1992). Also, the signals that reach institutions are generally more highly correlated than those that reach individuals (Lakonishok, Schleifer and Vishny, hereafter LSV, 1992). This increases the likelihood that institutional investors herd more than individual investors. In addition, fear of relative underperformance compared with the peer group of investment managers creates an explicit incentive for these managers to herd (Shleifer, 1985; Scharfstein and Stein, 1990).

Institutional herds are of particular interest as they can potentially impact the dynamics of asset prices (e.g., Chan and Lakonishok, 1995; Dennis and Strickland, 2002), and impose severe externalities on financial markets (e.g., Stein, 2009). For reasons of data availability, thus far the empirical literature has largely focused on mutual funds (e.g., Grinblatt, Titman and Wermers, 1995; Wermers, 1999; Coval and Stafford, 2007), and more recently on leveraged investors such as hedge funds (e.g., Reca, Sias, and Turtle, 2014). In contrast, relatively little is known about the investment behavior of pension funds. Yet, they constitute an increasingly large class of institutional investors and operate in an institutional setting which, particularly in recent years, imposes a set of constraints on their investment decisions (Domanski, Shin and Sushko, 2015). In turn, this not only makes their demands for assets highly inelastic, it might also induce a tendency for pension funds to herd.[1]

LSV (1992) produced one of the few studies to examine herding in the pension fund industry. They conclude that there is no evidence for herding in pension funds investment behavior, which

[1] Some recent studies argue that portfolio rebalancing and hedging activities by large institutional investors, such as pension funds, can eventually result in positive feedback loops, and can therefore pose severe risks for the stability of financial markets (*e.g.*, Haldane, 2014; Domanski, Shin and Sushko, 2015). For example, Malkhozov, Mueller, Vedolin and Venter (2015) show, both theoretically and empirically, that the hedging activity of investors in the US mortgage-backed securities market (i.e., which leads to their asset demands being highly inelastic) amplifies movements in long-term rates.

is perhaps surprising, since this differs from the experience of many other types of institutional investors. However, the conclusion of LSV (1992) is subject to the important caveat that: 'while there is very little herding in individual stocks and industries, there are times when money managers simultaneously move into stocks as a whole or move out of stocks as a whole. Since our dataset contains only all-equity funds, we cannot examine this type of herding' (LSV, 1992, p. 35). LSV also conjecture that, due to the structure of the pension fund industry, herding might be more prevalent among subgroups of pension funds rather than in aggregate, but their data did not allow them to test this interesting conjecture.

The primary goal of this paper is to address these issues in order to refine our understanding of the investment behavior of pension funds. First, we focus on pension fund herding in asset classes rather than in individual stocks. Second, we investigate whether herding is more predominant in subgroups; we classify pension funds into subgroups according to their size and sponsor type. Our analysis is made possible thanks to a unique dataset that covers UK private-sector and public-sector defined benefit (DB) pension funds' monthly asset allocations over the past 25 years. We have information on the funds' total portfolios and asset class holdings, and are also able to decompose changes in portfolio weights into valuation effects and flow effects.[2]

The empirical analysis establishes three sets of results about the herding behavior of pension funds. *First*, we address the question of whether pension funds herd, and our results provide robust evidence of herding in the asset allocations of pension funds. In particular, we document a positive relationship between the cross-sectional variation in pension funds' net asset demands in a given month and their net demands in the preceding month, providing support for the hypothesis that pension funds herd together in the very short term. These results are obtained using the test proposed by Sias (2004) and also confirmed using the original test of LSV (1992).

Second, we analyze how pension funds herd, and find strong evidence that pension funds herd in subgroups. Private-sector pension funds follow other private-sector funds more than public-sector funds, and public-sector funds follow other public-sector funds more than private-sector funds. Similarly, we find that pension funds tend to follow other funds of similar fund

[2]There are very few studies on pension fund flows, possibly because of the difficulty in obtaining reliable data until recently. Some examples are the papers of Sialm, Starks, and Zhang (2015a,b) which compare mutual fund flows of defined contribution plans with the fund flows of other mutual fund investors. Huberman and Sengmueller (2004) examine retirement plans' allocation of funds and transfers to or from company stocks. Of particular note for our study is Pennacchi and Rastad (2011), who show that career concerns often prevail over the optimal strategy of public-sector pension funds to immunize the risk of their liabilities. In their study, the asset allocation chosen by trustees and their consultants is largely driven by the performance of peer-group pension funds.

size. We then examine the effect of sponsor type controlling for size. We do this by double sorting funds by sponsor type (private-sector and public-sector) and by size (small, medium and large), and we find that public-sector funds follow other public-sector funds of similar size, while large private-sector funds strongly follow other large private-sector funds. Furthermore, the empirical evidence allows us to rule out the possibility that pension fund herding is due either to habit investing (i.e., serially correlated fund cash flows) or to momentum (i.e., positive feedback) trading.

Our findings suggest that it is unlikely that pension funds herd because of superior information. Indeed, our results indicate strong short-term *mechanical* portfolio rebalancing by pension funds. Two types of rebalancing are identified. First, there is mechanical rebalancing towards their long-term asset mix which, in turn, is driven by their liability. Although we do not have data on the pension funds' liabilities, we can draw inferences about the changing maturity of their liabilities from the longer-term dynamic asset allocation strategies pursued over the course of the sample period. Most private-sector plans have closed both to new members and to future accrual by existing members, whereas public-sector plans are still open. This implies that private-sector plans are more mature than public-sector plans of similar size. We document that, as the maturity of their liabilities has increased, private-sector pension funds have systematically switched from equities to conventional and index-linked bonds in line with standard asset-liability management (ALM). The analysis also suggests that the average pension fund – as represented by the peer-group benchmark – appears to choose the long-term asset mix which matches its liability profile. Second, our findings also indicate strong short-term mechanical portfolio rebalancing by pension funds, i.e., pension funds correct changes in portfolio weights resulting from short-term valuation changes that drive the weights away from the asset mix specified in their investment mandate.

Third, we investigate whether pension fund herding impacts asset prices, and uncover some evidence that pension funds exert a price impact and provide short-term liquidity to financial markets. However, we find that the price impact is not persistent. This, in turn, suggests that pension fund trades are largely uninformed, in the sense of not reflecting changes in expected returns, a finding that is largely consistent with our earlier results showing that pension funds rebalance their portfolios in a *mechanical* fashion. In the long term, there are systematic changes in the strategic asset allocation (SAA) of the average fund which reflect its changing liability structure. So there is little room for the average fund to react to changes in the expected returns and risks on the assets (which are the signals to which informed active managers would respond). Our results indicate that pension funds' investment behavior does not help move asset prices towards their fundamental values and, therefore, does not play a strongly stabilizing role on financial markets.

Finally, we examine pension funds' performance, and provide evidence that there are only small cross-sectional differences in returns across pension funds, consistent with widespread herding behavior by UK pension funds. We also document that the best performing funds are private and large. These funds tend to herd less, and follow more their own trades, than the other funds. Conversely, the worst performing funds tend to be small and have higher weightings in bonds relative to equities - a feature that is consistent with these funds being more mature.

To conclude the analysis, we investigate the market exposure of the average pension fund in our sample and find that the peer-group benchmark returns match very closely the returns on the relevant external asset-class market index. This result, coupled with the evidence on herding, supports anecdotal evidence that pension funds herd around the average fund which generates the peer-group average return and who is, in turn, no more than a 'closet index matcher'.[3]

The rest of the paper is organized as follows. Section 2 discusses the institutional features of the pension fund industry in the UK, and Section 3 describes our data in detail. Section 4 provides the core empirical results on pension funds' herding; we examine whether and why pension funds herd, and whether their herding activity exerts a price impact. Section 5.1 sheds light on some aspects of pension funds' performance. Finally, Section 6 concludes the paper. Further details are provided in the Appendix, and a number of extensions and robustness checks are reported in the Internet Appendix.

2 The UK Pension Fund Industry: Institutional Details

In this section, we first review the main regulatory and accounting reforms, which led UK pension funds to use liability-driven investment (LDI) strategies. Then, we describe the governance of UK DB pension funds. This description of the industry suggests naturally the possibility that pension funds follow other pension funds with similar characteristics into and out of the

[3]'Closet indexing' refers to the practice of some so-called 'active funds' having weights that differ very little from those underlying the benchmark index. A recent study by Cremers, Ferreira, Matos and Starks (2015) finds that closet indexing is common in the mutual fund industry.

same asset classes, i.e. they herd in subgroups.

Prior to the mid-1990s, UK pension funds were able to optimize the risk-return profile of their assets, since their liabilities were 'immature' and so could be disregarded when it came to setting the funds' investment strategy. Furthermore, for most of its history, the UK pensions industry was subject to a light-touch regulatory framework with little need for accounting transparency. After the mid-1990s, however, not only did the maturity of pension funds increase, but also a range of regulatory and accounting changes – the Pension Acts of 1995 and 2004, the 1997 Minimum Funding Requirement, and the 2000 Financial Reporting Standard 17 (which was superseded by the International Accounting Standard 19) – were introduced aimed at enhancing the resilience and transparency of the UK pension fund industry (Blake, 2003; Greenwood and Vayanos, 2010). All these changes had a strong influence on pension funds' ALM strategies, linking SAA much more closely to the development of plan liabilities. Pension funds became more likely to follow LDI strategies, reducing their historically high weight in equities and replacing these with conventional and inflation-linked government bonds, together with interest rate and inflation swaps.

The pension funds in our dataset invest the accruing contributions of DB pension plans. The pension plans have sponsors, namely the employers that established the plans for their retired employees, and the security of the pensions promised (i.e., the liabilities) depends on the assets backing the liabilities plus (in the case of plans in deficit where the value of the assets is less than the value of the liabilities) the strength of the sponsor covenant to make good the deficit over time. Standing between the sponsor and the plan beneficiaries are the plan trustees or fiduciaries. The trustees are nominated by the sponsor and a minority can be nominated by the beneficiaries, but they have a legal duty to act in the interests of the beneficiaries. In exercising this duty, they are advised by consultants, since most trustees are part-time and often do not have much investment or actuarial expertise. The consultants advise the trustees on the value of the liabilities and the strength of the sponsor covenant. They also advise trustees on the funding strategy needed to remove any deficit over an agreed period and the investment strategy.

The investment strategy has two components. The first is the SAA: the broad mix of asset classes intended to match the maturity profile of the liabilities. A young immature pension plan will invest heavily in equities and other growth assets. Then, as the plan matures, the SAA will switch to bonds and bond-like assets which have the stable cash flows needed to deliver the pensions in retirement.[4] This is generally regarded as the passive component of the investment strategy. The second component is the active component, i.e., the strategy of trading in and out of different asset classes and securities with the aim of generating additional returns beyond a passive strategy in order to reduce the sponsor's funding costs.

There are other institutional features of the UK pension fund industry which are important to the understanding of pension funds' investment behavior, and their tendency to herd in subgroups. *First*, the consultant will advise the trustees on both the SAA and the appointment of the investment managers. The consultant will typically express the SAA in terms of a benchmark comprising the main asset classes with weights that reflect the plan's maturity. The investment managers will be given an investment mandate that specifies their investment objectives. In particular, the mandate may contain a performance benchmark which, although is usually tailored to the circumstances of the fund, might also make reference to the investment manager's peer group.[5] As a result, trustees in different plans, but with similar characteristics, are likely to be given similar advice at the same time. This is also because consultants tend to specialize in funds of similar types, and the UK consultancy industry is much more heavily concentrated than in other parts of the world.[6] Thus, the advice that reaches pensions funds is highly correlated across funds of similar types, and this might induce pension funds to implement similar trades.

Second, managers can deviate from the SAA benchmark when they attempt to generate additional returns from the active strategies of security selection and market timing. However, there are limits to their investment freedom expressed in terms of a risk budget, which sets out how far they can depart from the benchmark. If the funds violate their risk budget, then they will *mechanically* rebalance their portfolios. The fund's risk budget, in turn, depends on the funding position and the strength of the sponsor covenant. Thus, investment managers in plans that are well funded with a strong sponsor will have a larger risk budget than those in plans

[4]As funds mature, they would be expected to move away from equities and into bonds, regardless of their funding status and sponsor covenant strength (Sundaresan and Zapatero, 1997; Lucas and Zeldes, 2009; Benzoni, Collin-Dufresne and Goldstein, 2007; Andonov, Bauer and Cremers, 2013).

[5]For example, the investment manager might be set the task of being in the first quartile of peer group performance over a specified horizon.

[6]In particular, the UK pension fund industry is much more concentrated than the US industry. LSV (1992) document that none of the independent investment counselors in the US pension group had a market share larger than 4 percent. In contrast, there are three large consultants in the UK and, in 1993, five fund managers accounted for about 80 percent of the market (Blake, Lehmann and Timmermann, 1999). The consultants advise a number of funds, many of which will be in similar positions in terms of funding ratios and maturity. Further, some consultants specialize in advising certain classes of pension fund, such as local authority (i.e., municipal) funds.

with a deficit and a weak sponsor. This implies that funds with similar risk budgets are likely to rebalance their portfolios at a similar time.

Third, the consultants and trustees do not interfere with the day-to-day decisions taken by the investment managers, but they will monitor their managers' investment performance, typically quarterly. The fear of underperforming the peer-group can, in turn, induce the fund manager to follow the asset allocation of their peers.[7] In addition, the high frequency of assessment against a peer-group benchmark may limit the extent to which pension funds engage in active management, which would also result in correlated trades among pension funds of similar maturity.

Fourth, different pension funds may well hire the same investment manager. It is also plausible that each investment manager will manage assets for different pension funds in a similar fashion. However, it is important to note that pension funds' mandates to investment managers are asset-class specific. Therefore, while the fact that multiple pension funds may be using the same investment manager which, in turn, can generate some form of herding at the level of individual securities, this does not have obvious implications for herding at the asset-class level. Indeed, as mentioned earlier, the decision on how to rebalance portfolios across asset classes is made by pension funds on the basis of advice from consultants. Put another way, investment managers receive mandates for discretionary asset management from pension funds which are specific with respect to, among other things, the asset class and the plan sponsor's level of risk tolerance, but they have no influence on how pension funds set the SAA.[8]

Testable Implications. The above discussion suggests that we should not be surprised to observe pension funds following each other into and out of the same asset classes, thus exhibiting herding behavior. A careful examination of the institutional setting, however, suggests that this herding is more likely to take place in subgroups. These subgroups should be defined in terms of the funds' maturity, investment mandates, risk budgets and choice of consultant.

Unfortunately we do not have data on these factors, but we conjecture that their impact can be well captured by fund size and sponsor type (private vs public). As we have mentioned,

[7]Short-term under performance and the failure to fulfill the original mandate are often the reasons why fund managers are dismissed (Financial Times, 2014). More generally, relative performance is used as a marketing device through which active investment managers compete for clients.

[8]It is common for specialist investment managers to be appointed for each asset class, especially in large plans. It used to be common, especially at the beginning of the sample period, for balanced managers to be appointed to manage across all asset classes; for small schemes, this is still the case. However, the SAA for each pension fund is still chosen by the consultant and the investment manager will be set a separate objective for each asset class.

consultants tend to specialize by size and type of fund, and investment managers tend to be assessed relative to funds of similar size and sponsor type. Furthermore, most of the private-sector plans are closed, whereas all the public-sector plans are still open. This implies that private-sector plans are likely to be more mature than public-sector plans of the same size. This will have implications for the SAA. Public-sector funds may also have a stronger sponsor covenant, as they benefit from an implicit government guarantee. The strength of the sponsor covenant, however, tends also to increase with the size of the fund. Therefore, smaller funds, particularly in the private sector, are likely to be associated with weaker sponsor covenants than larger funds.

Overall, given the institutional setting of the pension fund industry described above, we are interested in testing whether pension funds herd and how they herd, and in particular whether they follow each other into and out of the same asset classes in subgroups defined by sponsor type and fund size. Given the large size of pension funds, we are also interested in whether they exert an impact on asset prices.

It is important to note here that our definition of herding is somewhat different from what is typically considered herding in the literature. This is because pension funds might herd in asset classes for a number of reasons that are unrelated to the discretionary decisions of individual managers following their investment mandates, such as career concerns (e.g., managers' fears of underperformance) and the nature of pension fund investing (e.g., LDI and portfolio rebalancing). We consider this broader definition of herding because, although the reasons why pension funds display correlated trades might differ, the consequences in terms of, say, price impact are the same.

3 Data and Descriptive Statistics

The data used in this paper were provided to us by State Street Investment Analytics (SSIA hereafter) and consist of monthly observations on 189 UK DB pension funds from January 1987 to December 2012.[9] The data are in the form of an unbalanced panel, covering a total of 108 corporate and 81 local authority pension funds.[10] For each fund, we have data on the overall

[9]The SSIA is one of the two key performance measurement services in the UK, the other is CAPS (Combined Actuarial Performance Services). The SSIA database was originally owned by the WM Company.

[10]In this study, the terms corporate funds and private-sector funds, and similarly local authority funds and public-sector funds, are used interchangeably. Within the UK public sector, only local authority (municipal) employees have funded pension plans.

portfolio (i.e., total assets) and the following seven constituents: equities (UK and international), conventional bonds (UK and international), index-linked bonds (UK only), cash/alternatives, and property. Cash/alternatives is a catch-all residual category that includes, e.g., investment in both money market instruments and hedge funds; however, the investment in hedge funds is largely concentrated in the second part of the sample. For each asset class and each month, every fund reported initial market value, average fund value, dividend, return and net investment. We also have information on peer-group benchmark returns and the returns on the external market indices that SSIA uses in its analysis. The identities of the funds are unknown and we have no direct information on their liabilities. However, the changing asset weights over the sample period allow us to draw inferences about the development of the funds' liabilities over time. The dataset covers roughly one third by value of the UK pension fund industry as of 2012, and about half of all funds operating in the UK over the sample. Figure 1 shows asset holdings over the sample period by sponsor-type of pension fund, i.e., private-sector vs public-sector.

3.1 Pension Fund Returns and Asset Holdings

Table 1 presents summary statistics for the annualized monthly returns of the pension funds in our sample for 1987-2012. During this period, equities generated the highest average return (9.4 percent) and cash/alternatives the lowest (5.6 percent). The strong performance of equities is largely driven by the return on domestic rather than international equities. The median return on equities is substantially larger than the average return, a consequence of the dramatic fall in equity prices during the recent global financial crisis. The returns on both cash/alternatives and property are highly autocorrelated. The average returns in each asset class are broadly similar for both corporate and local authority pension funds, despite having substantially different asset allocations.

Figure 2 shows that, for corporate pension funds, the equity weighting decreased significantly from a peak of 79 percent in 1993 to 36 percent in 2012. Over the same period, their weighting in index-linked bonds increased from 3 percent to 15 percent, while their allocation to conventional bonds increased from 7 to 30 percent. The weightings to property diminished over the period. In contrast, the portfolios of local authority funds display rather more gradual shifts in allocations over the sample period, with their allocation to equities falling from 81 percent in 1993 to 62 percent in 2012. Their weighting in conventional and index-linked bonds were roughly 13 percent and 4 percent in 2012, respectively. The de-risking of corporates, which contrasts with the high exposure to equities maintained by local authorities, is consistent with their differing liability profiles. The plan closures in the private sector began in the late 1990s, first slowly and then more rapidly during the first decade of this century. The effect of closure is to increase rapidly the maturity of a pension fund's liabilities (by reducing the duration of the pension fund's projected net cash outflows in the form of pension payments). The stronger sponsor covenant in local authority plans, compared with corporate plans, arising from the taxation powers of local authorities, enables them to take more risk.[11]

Changes in the asset mix of pension fund portfolios can result either from valuation or flow (net investment) effects. Figure 3 presents the cumulative sum of both corporate and local authority pension funds' net investment in the various asset classes. There are two distinct phases of net investment in equities, one of which peaks in 1992 and the other in 2004. Net investment in conventional bonds has been substantial since 1994, except for the 2000-01 and 2008-09 stock market crashes. Purchases of inflation-linked bonds were particularly strong during the 1991-97 and 2003-07 periods. The net investment in property has been fairly stable for the whole period and especially during the 2008-12 period, although this has mainly been by local authorities.

The government ended the tax relief that pension funds could claim on UK dividend payments in 1997 and this encouraged pension funds to switch out of UK equities into international equities. By 2005, pension funds (in aggregate) held a larger fraction of international equities than UK equities. Figure A1, in the on line appendix, shows very different net investment behavior by private- and public-sector funds, mainly because of their different maturities. Corporate funds began disinvesting from UK equities in 1998 and, although they switched into international equities, growth in this category slowed significantly after 2004. In contrast, local authority funds actually increased their holdings of UK equities after 1998 and only began to disinvest after 2010; their net investment in international equities grew very rapidly starting from 1998. The two fund types exhibit similar behavior when it comes to bonds, however, as Figure A2, in the on line appendix, shows. Their allocations to UK conventional bonds began to grow after 1995, to UK index-linked bonds after 1991, and to international bonds after 1989.

[11]Such risk taking behavior is also common in US public sector funds, which actually increased their investments in equities and alternatives from 57% to 73% between 1993 and 2010 (Cohen, 2014).

3.2 Peer-Group and External Benchmarks

The two main types of benchmarks used in the UK to evaluate pension fund performance are external asset-class benchmarks and peer-group benchmarks. In the early 1970s, when performance measurement started, most pension funds selected customized benchmarks which were based on external indices with weights tailored to the specific objectives of the fund. Interest in how other pension funds were performing quickly led to the introduction of peer-group benchmarks. Since the mid-2000s, an increasing number of funds returned to customized benchmarks to reflect the maturity profile of their liabilities. However, for most of our sample period, peer-group benchmarks dominated.[12] Even where a fund has a customized benchmark, it is possible that this is set to equal the peer-group benchmark, as long as the asset mix of the latter approximately matches the fund's specific circumstances (WM Company, 1997).

Each month, SSIA collects individual fund returns and weights, and aggregates them into peer-group benchmark weights and returns. Peer-group benchmarks, therefore, are based on the universe of funds monitored by SSIA. Unfortunately, SSIA did not keep full records of this information for the early years. As a result, our dataset includes a smaller number of funds than the entire universe of funds used by SSIA to construct peer-group benchmark returns which, in turn, is a subset of the whole population of funds in existence in the UK. However, the dataset is representative both of the whole universe of funds monitored by SSIA and of the full set of funds operating in the UK over the sample period. In other words, there is neither survivorship bias nor selection bias in our data.[13]

External indices have the virtues of being independently calculated and immediately publicly available. However, the weightings of the securities in these indices can be substantially different from the pension funds' own weightings of these securities; this is the case in particular for cash, international bonds and equities (Blake and Timmermann, 2005). The set of external

[12]We should note, however, the differing behavior of private- and public-sector funds. Public-sector funds have remained wedded to peer-group benchmarks for most of the period, due to peer-group pressure and the publication of local authority league tables, allied to the fact that they remain open to new members. It is mainly private-sector funds that have switched to customized benchmarks in recent years.

[13]The absence of survivor bias can be seen by comparing the summary statistics on the peer-group benchmark returns, displayed in Table A1 in the Internet Appendix, with the statistics on the returns of the average fund, resulting from aggregating the returns of the individual funds available in the dataset for each month, displayed in Table 1. We find that the differences are negligible, both in aggregate and also when looking separately at the summary statistics of the corporate and local authority funds. Further, SSIA covers about half of all pension funds in the UK by number, with the rest monitored by CAPS. There is no selection bias in our dataset, since any switching between these two providers (say as a result of a change of consultant or fund manager) will be symmetric (Tonks, 2005; and Blake, Rossi, Timmermann, Tonks and Wermers, 2013). Specifically, each year, some funds will switch from SSIA to CAPS, while other funds will switch in the opposite direction. These switches are not driven by the funds' performance, and, anecdotally, are fairly random.

indices used by SSIA to assess the performance of the pension funds in its universe comprises: Financial Times Actuaries (FTA) All-share Index (UK equities); FTA World (excluding UK) Index (international equities); FTA British Government Stocks All-Stocks Index (UK fixed-income bonds); JP Morgan Global (excluding UK) Bond Index (international bonds); FTA British Government Stocks Index-Linked All Stocks Index (UK index-linked bonds); LIBID (London Inter-Bank Bid Rate) 7-day deposit rate (cash/alternatives); and Investment Property Databank (IPD) Annual Property Index (property). All these indices are denominated in UK pounds, assume that investment income is reinvested (gross of tax), and returns are calculated on a time-weighted basis and are available on Datastream.

4 Herding

Previous studies on institutional herding largely focused on herding in the same security, in certain types of security, or in similar industry groups. However, the structure of the pension fund industry, described in Section 2, suggests that herding is most likely to manifest itself at the asset-class level, e.g., pension funds following other pension funds out of equities and into bonds at the same time. Also, peer-group weights are published monthly by SSIA by asset class and not by individual security holdings, which makes herding more likely at the level of asset class than at the level of individual securities. In this section, we provide our core results on whether and how pension funds herd, and on whether their trading activities impact asset prices.

4.1 Do Pension Funds Herd?

We test whether pension funds herd into and out of an asset class using standard herding tests, previously applied to test herding in individual stocks and in industry groups (Sias, 2004; and, Choi and Sias, 2009). The testing procedure is based on the idea that, if pension funds herd, the cross-sectional variation in pension fund net investment in a particular asset class in a given month will be positively correlated with the cross-sectional variation in net investment in the previous month. However, it is clear that such positive correlation is not sufficient to establish herding, as it is also consistent with pension funds following their own previous month trades. This is an issue we address later in the analysis.

Specifically, for each month, the raw fraction of pension funds buying asset class j is defined as:

$$Raw\Delta_{j,t} = \frac{\text{No. of funds buying asset } j \text{ at time } t}{(\text{No. of funds buying asset } j \text{ at time } t + \text{No. of funds selling asset } j \text{ at time } t)} \tag{1}$$

where the fund is identified as a buyer of asset j when it has a positive net investment (or flow). To facilitate the analysis, it is convenient to standardize this 'raw fraction of institutions buying asset class j' as follows:

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

where $\overline{Raw\Delta_t}$ is the cross-sectional average (across J asset classes) of the raw fraction of institutions buying in month t, and $\sigma\left(Raw\Delta_{j,t}\right)$ is its cross-sectional standard deviation (across J asset classes). The institutional herding test is based on the following cross-sectional regressions carried out at each time t:

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

A positive and significant β_t is consistent with pension fund herding. Table 2 (Panel A) reports the time-series average of the estimated coefficients (β_t) resulting from the cross-sectional regressions. Specification (1) focuses on the seven asset classes: UK and international equities, UK and international bonds, UK index-linked bonds, cash/alternatives and property. Specification (2) excludes the catch-all category cash/alternatives from the analysis. We find that the average β_t is around 44 percent in Specification (1), and this increases to 47 percent in Specification (2). The large t-statistics indicate that these coefficients are strongly statistically significantly different from zero, clearly rejecting the null of no herding (i.e., average β_t=0).

However, these results should be taken with caution because a positive β_t is not complete proof of pension fund 'herding', as it is also consistent with 'funds following their own trades'. This is because β_t aggregates very different information which can be decomposed into two parts: (1) pension funds following themselves into and out of the same asset classes over adjacent months (*following their own trades, o*), and (2) pension funds following other pension funds (*herding, h*). The correlation captured by β_t can be partitioned accordingly into these two components, denoted by β_t^o and β_t^h. Analysis of the two components β_t^o and β_t^h allows us to carry out a more accurate test by obtaining a more precise estimate of the herding component.

Specifically, β_t can be written as:

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

where J is the number of asset classes; $N_{j,t}$ is the number of pension funds trading asset class j at time t; $D_{n,j,t}$ is a dummy variable that equals unity (zero) if pension fund n buys (sells) asset class j at time t; and $D_{m,j,t}$ is a dummy variable that equals unity (zero) if pension fund m buys (sells) asset class j at time t. Equation (4) shows that β_t is the sum of two terms: $\beta_t = \beta_t^o + \beta_t^h$. The first term ($\beta_t^o$) denotes the *following your own trades* component, while the second term (β_t^h) denotes the *pure herding* component. Intuitively, the first term takes positive values if pension fund n buys asset class j at times $t-1$ and t, or sells at times $t-1$ and t. In contrast, if individual pension funds' transactions at time t are independent of their transactions at time $t-1$, this term will be zero. The second term takes positive values if pension fund n buys (sells) asset class j at time t and pension fund m also bought (sold) asset class j at time $t-1$. In contrast, if pension fund n's transaction at time t is independent of pension fund m's transaction at time $t-1$, then β_t^h will be zero.

Panel A of Table 2 presents the two components and their t-statistics: both β_t^o and β_t^h are positive and strongly statistically significantly different from zero, with t-statistics exceeding 20 in each specification. However, they are also statistically different from each other as β_t^h is much larger than β_t^o (more than 10 times larger). Thus, while there is evidence of pension funds following themselves, the pure herding effect strongly dominates.[14]

4.2 Why Do Pension Fund Herd?

Thus far, we established that pension funds tend to follow other funds' trades more than their own trades. However, herding of pension funds can manifest itself in different ways. For

[14] The above analysis is carried out with monthly data in order to exploit the higher number of observations available; however, the results are qualitatively the same when using quarterly data.

example, it could result from correlation between investor cash flows (so-called habit investing), or it could be related to momentum trading, or it could be induced by the institutional settings of the industry, as described in Section 2. The latter can incentivize pension funds to follow similar fund types (herding in subgroups). In what follows, we shed light on these three potential features of herding behavior.

4.2.1 Habit Investing

The tests involving eqs. (3) and (4) that are based on pension funds buying or selling a particular asset class j (i.e., based on flow information) may be influenced by the presence of cross-sectional and time-series correlations in the cash inflows into pension funds. On the one hand, if new cash flows into pension funds are correlated, and pension funds then invest these cash flows in line with their existing portfolio weights, this will result in pension funds moving into and out of the same asset classes over adjacent periods. On the other hand, suppose that a subset of pension funds have similar portfolio weights on account of their similar liability structure, and cash flows into these pension funds are correlated not only over time, but also across funds (so these pension funds invest the new cash flows to maintain their existing portfolio weights). Then, according to the test of eq. (4), these pension funds will appear to follow other pension funds into and out of the same asset classes over adjacent periods, apparently indicating herding. However, a positive correlation may simply reflect correlated cash flows rather than herding.

We therefore investigate whether our results are driven by correlated cash flows into pension funds. We do this by focusing on changes in portfolio weights. Pension fund n is classified as a buyer of asset class j if, in that period, the fund *increased* its return-adjusted weight in asset j. Specifically, following Blake, Lehmann and Timmermann (1999), changes in (log) portfolio weights can result either from valuation effects (i.e., return differentials) or from net investment effects (i.e., net cash flow differentials):

$$\Delta \log(\omega_{n,j,t}) \simeq (r_{n,j,t} - r_{n,p,t}) + \left(ncf_{n,j,t} - ncf_{n,p,t}\right) \tag{5}$$

where $\omega_{n,j,t}$ is the weight of asset j in the portfolio of pension fund n; $r_{n,j,t}$ and $ncf_{n,j,t}$ are the rate of return on pension fund n's holdings of asset class j and the rate of net cash flow into asset class j; $r_{n,j,t}$ and $ncf_{n,p,t}$ are the value-weighted total return on and rate of net cash flow into pension fund n during month t. We then define $ncf_{n,j,t}-ncf_{n,p,t}$ as the change in the return-adjusted weight. We classify pension fund n as a buyer (seller) of asset class j if the return-adjusted weight of asset class j increased (decreased) between time $t-1$ and t. In other words, we are interested in identifying the change in weight in asset j that is due to pension fund n buying asset j, rather than the change in weight that is due to the return on asset j exceeding the average return on the portfolio. Then, the raw fraction of pension funds increasing their weight in asset j at time t is defined as:

$$RawW\varDelta_{j,t} = \frac{\text{No. of funds with increased return-adjusted asset weight } j \text{ at time } t}{\begin{array}{c}(\text{No. of funds with increased return-adjusted asset weight } j \text{ at time } t \\ + \text{ No. of funds with reduced return-adjusted asset weight } j \text{ at time } t)\end{array}}. \quad (6)$$

We now repeat the same steps as before: we first standardize $RawW\varDelta_{j,t}$, and then estimate eq. (3) by regressing the standardized fraction of pension funds increasing their weight in asset j at time t (denoted $\widetilde{\varDelta}_{j,t}$) on the standardized fraction of pension funds increasing their weight in asset j at time $t-1$ (denoted $\widetilde{\varDelta}_{j,t-1}$). If the estimated average correlation is driven by correlated flows (habit investing), we would no longer expect a positive and significant correlation when replacing flows with return-adjusted weights as a measure of pension fund demand. Panel B of Table 2 shows that the correlation coefficient is actually greater than before, and clearly statistically significant at the 5 percent significance level, irrespective of the specification used. In fact, the difference between the 'following others' (or herding) and the 'following your own trades' component increases from 38 percent to 50 percent. This result makes sense given that benchmarks are set in terms of weights rather than flows. The implication of this result is that we can rule out habit investing as a source of herding for pension funds.

4.2.2 Herding in Subgroups

Herding can manifest itself in a number of ways and the discussion of the institutional features in Section 2 suggests that it can occur in subgroups defined by fund size and sponsor type. For example, it might be the case that private-sector funds largely follow other private-sector funds, and public-sector funds largely follow other public-sector funds. This might be due, for example, to the fact that peer-group benchmarks are tailored to the sponsor type, implying that pension funds should be more likely to follow similar fund types than different types. Therefore, we decompose the 'following others' measure into a 'following others of the *same* type' and 'following others of a *different* type'. To avoid distortions caused by differing numbers of investors in each group, we focus on *average* rather than absolute contributions to the 'following others' component – see Sias (2004) for a discussion of this point. We therefore measure private-sector (public-sector) funds' average contribution from following other private-sector (public-sector) funds and the average contribution from following public-sector (private-sector) funds. The average same-type herding contribution for private-sector funds at time t is derived from the second term in eq. (4) which is now limited to private-sector funds averaged over the J asset classes:

$$\text{Avg same-type}_{\text{t}}^{\text{C}} = \frac{1}{J}\sum_{j=1}^{J}\left[\sum_{n=1}^{C_{j,t}}\sum_{m=1,m\neq n}^{C^*_{j,t-1}}\left(\frac{D_{n,j,t}-\overline{RawW\Delta_t}}{C_{j,t}}\times\frac{D_{m,j,t-1}-\overline{RawW\Delta_{t-1}}}{C^*_{j,t-1}}\right)\right], \quad (7)$$

where $C_{j,t}$ is the number of private-sector funds trading asset class j in month t; $C^*_{j,t-1}$ is the number of other funds of the same type, i.e., other private-sector funds, trading asset class j in month $t-1$; and the remaining variables are defined as in eq. (5).[15] Similarly, the average *different*-type herding contribution for private-sector funds at time t is derived from the second term in eq. (4), but limited to private-sector funds following public-sector funds averaged over the J asset classes:

$$\text{Avg different-type}_{\text{t}}^{\text{C}} = \frac{1}{J}\sum_{j=1}^{J}\left[\sum_{n=1}^{C_{j,t}}\sum_{m=1,m\neq n}^{LA_{j,t-1}}\left(\frac{D_{n,j,t}-\overline{RawW\Delta_t}}{C_{j,t}}\times\frac{D_{m,j,t-1}-\overline{RawW\Delta_{t-1}}}{LA_{j,t-1}}\right)\right], \quad (8)$$

where $LA_{j,t-1}$ is the number of public-sector funds trading asset class j in month $t-1$. For example, if private-sector funds' underperformance concerns drive their herding, then the average *same*-type herding contribution will exceed the average *different*-type herding contribution. The same-type and different-type averages for public-sector funds are computed in the same fashion.

Panel A of Table 3 shows that there is evidence of herding in subgroups defined by sponsor type, i.e. the difference between 'following others of the *same* type' and the 'following others of a *different* type' is positive and statistically significant over consecutive months. In fact, private-sector funds' tendency to follow other private-sector funds (0.52%) exceeds their tendency to follow public-sector funds (0.42%). The evidence is even more compelling for public-sector

[15]Note that in light of the discussion in Section 4.2.1, in what follows, the analysis is based on return-adjusted weights ($RawW_{j,t}$) rather than flows ($Raw_{j,t}$). Thus, $\overline{RawW\Delta_t}$ is the cross-sectional average (across J asset classes) of the raw fraction of pension funds increasing the return-adjusted weight in month t.

funds (1.24% vs. 0.43%). Thus, herding by sponsor type is strong, and is particularly so for public-sector funds.

Pension funds may also herd more with funds of similar size, since the performance of the funds are generally evaluated against that of funds of similar size, given that fund size is also an important determinant of the strength of the sponsor covenant, among other factors.[16] Therefore, we group funds into size terciles according to their total assets. We do this for each month t, since funds might migrate from one group to another as funds enter or exit the sample. We have three groups of funds: small, medium and large. For example, in the case of small funds, *same* is denoted by small funds following other small funds, whereas *different* is denoted by small funds following either medium or large funds (see eq. (A.1) and (A.2) in Appendix A). A similar classification procedure applies to medium and large funds. In Panel B of Table 3, we report strong evidence supporting the existence of a size effect, that is large funds follow other large funds, medium funds follow other medium funds, and small funds follow other small funds.

Thus far, we have documented that both private- and public-sector funds herd by sponsor type, and we also found strong evidence in favor of a size effect. Next, we examine the interaction between size and sponsor type. Indeed, according to the industry description in Section 2, the size and sponsor type effects in some cases might reinforce each other, while in other cases one effect might prevail over the other. We therefore test whether the results for herding by sponsor type change when conditioning on fund size. Specifically, we now perform a 3×2 double sort where we first divide the funds into terciles according to their size (small, medium, large) and then according to their sponsor type (private, public) – see eq. (A.3) and (A.4) in Appendix A. So in the case of small private-sector funds, for example, we restrict the categories of *other-same* funds to small-private funds and *other-different* funds to small public-sector funds – see eq. (A.5) in Appendix A. In this way, we refine the results of herding in subgroups in Table 3 by comparing funds of different-sector type but of similar size, thus accounting for the interaction between size and type.

Table 4 shows that, once we condition on size, the results for public-sector funds change little, with public-sector funds tending to follow other public-sector funds of similar size. In contrast, the result for small private-sector funds change substantially. We find that small private-sector

[16] Size is, in fact, an important determinant of pension fund asset allocation. Portfolio return volatility is highly negatively correlated with fund size, possibly reflecting the fact that small funds are generally less diversified than large funds (Blake, Rossi, Timmermann, Tonks and Wermers, 2013).

funds tend to follow other small funds *regardless of their type*. Thus, for small private-sector funds, the size effect prevails over the sponsor-type effect. However, large private-sector funds and to a lesser extent medium private-sector funds tend to follow mostly other funds of similar type. What is common across large private- and public-sector funds though is that the type effect strongly prevails. Thus, large funds mainly herd with funds of similar type.

These results, taken together, provide strong evidence that pension funds herd in subgroups, defined by fund size and sponsor type.

4.2.3 Momentum Trading vs. Portfolio Rebalancing

A large body of literature has investigated momentum trading and found evidence that some groups of institutional investors are momentum traders.[17] This literature has mostly focused on mutual fund momentum trading at the security or industry level. Of particular relevance to our case is the study by LSV (1992), which finds that pension funds appear to follow neither positive- nor negative-feedback trading strategies, on average.[18] We now investigate pension funds' momentum trading at the level of asset classes.

Momentum trading might be viewed as a form of herding where pension funds herd into (away from) asset classes with high (low) past returns. If pension funds are momentum traders, there might be an omitted variable in eq. (3) that is correlated with the lagged demand of pension funds, so that lagged demand may simply proxy for lagged returns. We investigate this possibility by simply adding lagged returns to eq. (3). Specifically, testing for momentum trading requires estimating:

$$\mathit{\Delta}_{j,t} = \beta_{1,t}\mathit{\Delta}_{j,t-1} + \beta_{2,t} r^{PG}_{j,t-1} + \varepsilon_{j,t}, \tag{9}$$

where $r^{PG}_{j,t-1}$ is the peer-group return of asset class j at time $t-1$, and testing whether $\beta_{2,t}$ is positive. A positive $\beta_{2,t}$ coupled with a statistically insignificant $\beta_{1,t}$ would imply that herding is driven by momentum trading. However, we find no evidence of momentum trading by pension funds, as reflected in a generally statistically significant negative $\beta_{2,t}$.[19] Moreover, the coefficient on lagged demand, $\beta_{1,t}$, is generally unchanged, i.e., the inclusion of lagged returns does not

[17] See, for example, Grinblatt and Titman (1989, 1993), Grinblatt, Titman and Wermers (1995), Nofsinger and Sias (1999), Wermers (1999, 2000), Sias, Starks and Titman (2006), and Choi and Sias (2009).

[18] LSV find some evidence of momentum trading in small-cap stocks, but these represent only a tiny fraction of pension funds' total assets.

[19] Table A3 in the Internet Appendix presents the estimated coefficients. Also note that the results are robust to replacing the peer-group return ($r^{PG}_{j,t-1}$) with the corresponding external index return for asset j, constructed as described in Section 3.2.

alter the estimated impact of lagged demand. In essence, our results corroborate the findings of LSV (1992) in this aspect.

Therefore, based on the test proposed by Sias (2004), we established that pension funds seem not to engage in momentum trading, rather they seem to behave as contrarian investors, as indicated by the negative coefficient ($\beta_{2,t}$) in eq. (9), which, in turn, might be consistent with portfolio rebalancing. It is important to establish whether pension fund herding results in procyclical or positive-feedback investment strategies – buying assets in a rising market, selling in a falling market – given that such strategies could exacerbate price movements in financial markets (LSV, 1992; and Wermers, 1999). In contrast, if pension funds were to rebalance their portfolios in response to market movements, they would provide short-term liquidity to the markets.

To shed further light on this issue, we perform two additional exercises.[20] *First*, we employ the methodology used by Blake, Lehmann, and Timmerman (1999). As eq. (5) shows, changes in portfolio weights can result either from valuation changes (return differentials) or from changes in the asset allocation (net investment differentials). Panel A in Table 5 shows that pension funds decrease their portfolio weight in equities (with an average annual change of -1.70%), and also switch between domestic equities (-3.56%) and international equities (0.37%). However, the rebalancing away from domestic equities is attenuated by the fact that, on average, pension funds experience positive valuation changes in domestic equities (0.64% p.a.). In contrast, the increase in the weight of bonds (5.06%) is largely driven by positive net investment in this asset class, since the valuation effect is generally negative. The variance decomposition (shown in the last three rows of each panel) reveals that valuation effects are important drivers of changes in portfolio weights, but over the full period, flow effects prevail over valuation effects in determining changes in the weights of international bonds and cash/alternatives. The changing weights in the various asset classes are consistent with the increasing maturity of pension funds.

A negative correlation between returns and net investment differentials, corr(r_t, ncf_t), is indicative of short-term portfolio rebalancing (see Blake, Lehmann, and Timmerman, 1999). Table 5 shows that rebalancing is especially strong in domestic equities, although it is also

[20]Note that, next, we focus on the 1995-2012 period, rather than the full 1987-2012 period for a number of reasons. In particular, the 1995 Pensions Act led to substantial changes in pension fund allocations with an increasing focus on liability-driven investing; prior to its introduction, pension fund asset allocations were mainly driven by risk-return considerations (see Section 2). The second reason is more practical: by restricting the analysis to the period after 1995, we can work with a more homogeneous data sample which allows us to obtain more precise estimates of pension funds' exposures. However, our results are qualitatively similar when using the full sample.

substantial in the other asset classes. The only exception is property, where the sluggish response of pension funds to valuation changes is likely to be explained by the low liquidity of property markets. Panel B shows a very different pattern of rebalancing during the crisis period, with net investment being negative in all asset categories except cash/alternatives and property.[21]

Second, we complement the analysis of Table 5 by regressing the flow component of changes in portfolio weights on the market and liquidity factors. We therefore include a liquidity factor in addition to the market returns to assess pension funds' exposure to liquidity conditions. This is because, given the long-term nature of pension fund liabilities, some groups of funds should be in a better position to take on liquidity risk. The external market indices were discussed in Section 3.2, so here we focus on our measure of liquidity.

Defining and then measuring liquidity are non-trivial exercises, and there is no single measure that can capture its full complexity. Market liquidity encompasses a number of transactional properties of markets, such as tightness, depth and resilience (Kyle, 1985). Moreover, market liquidity is intimately linked to funding liquidity, i.e., the ease with which market makers can obtain funding for their inventories of securities (Brunnermeier and Pedersen, 2009). We therefore attempt to capture liquidity by using an aggregate measure that combines several commonly used measures of liquidity. Specifically, we take the first principal component of the following liquidity measures: the negative of the change in the US TED spread, the negative of the change in the UK TED spread, the Pastor and Stambaugh (2003) liquidity measure, the negative of the change in the VIX volatility index, and the negative of the change in the noise measure of Hu, Pan, and Wang (2013). Details of the individual measures are presented in Appendix B. Specifically, we estimate:

$$\widetilde{NCF}_{j,t} \equiv ncf_{j,t} - ncf_{p,t} = \alpha + \sum_{s=0}^{3} \beta_s Mkt_{j,t-s} + \sum_{s=0}^{3} \gamma_s Liq_{j,t-s} + \varepsilon_t, \tag{10}$$

where $ncf_{j,t}$ and $ncf_{p,t}$ are the average fund's net cash flow rates into asset class j and the total portfolio, respectively, during month t; $Mkt_{j,t-s}$ is the return on the external market index j at

[21] In the Internet Appendix, Table A2 shows the decomposition of changes in asset weights separately for private- and public-sector funds. Of particular interest is the dramatic decrease in equity weighting by private-sector funds during the crisis that is largely driven by strong negative net investment (outflow) effects. Moreover, though private-sector funds' allocation to international bonds is fairly constant, this masks substantial positive valuation changes that are offset by negative flow effects.

time $t-s$; and Liq_{t-s} is the time $t-s$ measure of liquidity, as described in Section 5.2.[22,23] Panel A of Table 6 reports the aggregate market ($\Sigma\beta = \sum_{s=0}^{3} \beta_s$) and liquidity ($\Sigma\gamma = \sum_{s=0}^{3} \gamma_s Liq_{t-s}$) effects, in addition to the individual β_s and γ_s coefficients. There is overwhelming evidence that pension funds rebalance their portfolios in response to valuation changes, i.e., they behave like contrarian investors in that they increase (decrease) the return-adjusted weight in asset class j in response to negative (positive) valuation changes, which are proxied by negative (positive) returns in the external index associated with asset class j. This is true for equities and especially for bonds, although not for property, again for liquidity reasons. Pension funds also increase their allocation to most asset classes (with the exception of international bonds), but especially to international equities during periods of increased liquidity.

The constant terms in these regressions have an important interpretation. Recall that the dependent variable captures the component of the change in weight that is due to flow effects. As a result, the constant measures the time trend in a dynamic model of return-adjusted weights. It therefore provides useful information about the long-term SAA of pension funds. The negative constant on UK equities and the positive constant on bonds, for example, reflect de-risking (i.e., increased maturity matching) that is mainly driven by private-sector funds over the period. The positive constant on international equities reflects the switch from domestic to international equities following the ending of tax relief on UK equity dividends in 1997. The positive constant on index-linked bonds reflects the increasing focus on LDI. Overall, this simple model is particularly useful for identifying the key determinants of pension funds' allocation in equities, with R^2s of roughly 20 percent.

Panel B shows that the explanatory power of the model increases during the crisis period but qualitatively the results are largely unchanged: we again find evidence of a strong rebalancing effect, although this effect is no longer present for UK index-linked bonds. Further, pension funds significantly decrease their allocation to international equities, UK bonds and cash/alternatives as liquidity dries up. The results for property are rather different, however, as pension funds tend to increase their allocation to this asset class not only when the external property index increases, but also when global liquidity conditions deteriorate.

[22] Note that we do not have information on peer-group benchmark net investment flows, as the benchmarks only provide direct information on value weights and returns. Thus, we cannot perform the peer-group benchmark regressions as we did previously for returns. However, we can construct the flow of the average fund based on individual fund flows, and the average fund's flow is comparable to a hypothetical peer-group benchmark flow.

[23] We allow for lags in the right-hand side variables to account for the persistence in the evolution of the flows. This persistence may reflect pension funds' reluctance to rebalance every month, and their tendency to adjust their portfolios only when the actual asset allocation differs significantly from the desired asset allocation.

Overall, the results reported in this section suggest that pension funds herd strongly in subgroups defined by fund size and sponsor type, as one would expect given the institutional setting of the industry in which they operate. Their herding behavior is not related, however, to either habit investing or momentum trading, but rather to portfolio rebalancing.

4.2.4 Further Analysis

We subject the previous analysis to two additional exercises. First, we investigate the possibility that our findings might be driven by the fact that the herding analysis is based on only a small number of asset classes (compared with earlier studies which instead tend to focus on a large number of individual securities) and may also be distorted by an adding-up constraint. One concern, therefore, is whether the herding test employed here displays size distortion (a high probability of rejecting the null hypothesis of no herding when the null is true, i.e. type I error). To investigate this issue, we simulate the portfolio for a fixed number of funds (189 equal to the number of funds in our dataset), but for different number of asset classes, under the null of no herding. We perform 50,000 iterations; see Section A.II, in the internet Appendix, for a detailed description of the simulations.

If the Sias' test works well and displays no size distortion, it should produce a test size of around 5 percent. Table A4 shows the 95 percent critical values from the empirical distribution, together with the associated test size, obtained by performing the Sias' test on the simulated portfolio flows (Panel A) and on portfolio weights (Panel B). Our analysis suggests that, regardless of the number of asset classes considered, the Sias' test does not suffer from any size distortion. Moreover, the fact that these findings hold regardless of whether the test is based on portfolio flows or weights (also in the case of only 5 asset classes) allows us to conclude that the Sias' test works reliably, and does not suffer from any size distortion, even in the presence of an adding-up constraint.[24]

Second, we repeat the herding analysis using the original measure proposed by LSV (1992) (LSV measure, thereafter). The LSV measure tests for cross-sectional temporal dependence only indirectly, by looking at institutional trades within the same month, while the statistic of Sias (2004) tests directly for cross-sectional temporal dependence, by looking at investors'

[24]In the paper, we perform the analysis on return-adjusted weights, which are not subject to any adding-up constraint. It is possible for return-adjusted weights to increase for all asset classes simultaneously, which is not, of course, possible for portfolios weights. Therefore, as a further check, we also conducted the simulations on portfolio weights directly and still found that the Sias' test does not suffer from low power, and thus we can exclude that the test is subject to any size distortion, also in the presence of an adding-up constraint.

trades over subsequent months. The LSV measure for month t and asset class j is defined as:

$$H(j,t) = |Raw\Delta_{j,t} - \overline{Raw\Delta_t}| - AF(j,t), \tag{11}$$

where $Raw\Delta_{j,t}$ is the raw fraction of pension funds buying asset class j in month t, $\overline{Raw\Delta_t}$ is the expected proportion of funds buying in that month relative to the number of active funds, and $AF(j,t)$ is an adjustment factor for asset class j in month t, which accounts for differing numbers of active funds from month to month. Even if pension funds did not display cross-sectional temporal dependence, the expected value of $|Raw\Delta_{j,t} - \overline{Raw\Delta_t}|$ could be greater than zero, indicating herding. The adjustment factor $AF(j,t)$ will be large when there are only a small number of funds that are active in asset class j in month t. Specifically, $AF(j,t)$ is computed by assuming that the number of funds buying asset class j in month t follows a binomial distribution with probability $\overline{Raw\Delta_t}$ (see LSV, 1992, for details).

Table A5, Panel A, presents the LSV measure for each of the seven asset classes and the total portfolio, with (Tot.) and without (Tot. ex CA) the cash/alternatives class. The LSV measure is computed for each asset class and month; we then report the time-series averages, together with the associated t-statistics. We again find that, also according to the LSV measure, pension funds herd in asset classes. Panel B shows similar results for the analysis performed on return-adjusted weights. However, unlike the Sias' test, the LSV measure does not allow us to determine whether this result is due to pension funds following their own trades or other funds' trades, or whether pension funds herd in subgroups, which is fundamental to our analysis. For this reason, we prefer to use the Sias' test for our core analysis.

4.3 Price Impact

Thus far, we have documented that pension funds both herd and mechanically rebalance their portfolios in the short term. A related issue is whether this trading behavior generates a price impact. The typically large size of pension fund trades, coupled with pension fund herding behavior and their inelastic demand for assets, would suggest that they are in a position to influence asset-price dynamics, particularly in the market where they are big operators. We start by asking whether there is a price impact resulting from the trading activity of pension funds and, if this is the case, whether such a price impact is persistent.

We address both questions by examining the relationship between pension fund demand shocks and both contemporaneous and subsequent returns, given a set of controls. We use a similar methodology to Dennis and Strickland (2002), among others. We differ, however, in that we look at the price impact on index returns rather than at the level of individual securities. This will affect the set of controls we employ, but the spirit of the test remains the same. Furthermore, we restrict the analysis to UK asset classes, as we expect any price pressures exerted by UK pension funds to have a stronger impact on domestic than international markets. Specifically, we organize our analysis around the following regression:

$$r_{j,t+h} = \gamma_{j,0} + \gamma_{j,1} CF_{j,t} + \gamma_{j,2} Z_{j,t} + \epsilon_{j,t} \tag{12}$$

where $r_{j,t+h}$ is the return in month $t+h$ of asset class j for h =0,...,12; $CF_{j,t}$ is the net investment of UK pension funds into asset class j in month t, which is divided by the standard deviation that is computed over a five-year rolling window; and, $Z_{j,t}$ is the set of control variables, which vary with the market considered. The set of control variables for UK equities include lagged equity returns (to capture momentum effects), dividend yields, term spreads, and realized equity return volatility. The set of control variables for UK bonds include lagged bond returns, term spreads, the short rate, the five-year break-even inflation rate, and realized bond return volatility.

The results, displayed in Figure 4, show that pension funds trade in the opposite direction to market movements, therefore providing short-term liquidity to the markets. Specifically, consistent with Lipson and Puckett (2006), we find that pension funds are net sellers (net buyers) in months when markets experience price increases (decreases). In fact, for $h = 0$, the $\gamma_{j,1}$ coefficient is negative, and statistically significant, across asset classes. However, the price impact is not persistent, since for $h \neq 0$, the $\gamma_{j,1}$ coefficients are no longer statistically different from zero. The absence of an effect that is persistent, in turn, suggests that pension fund trades are uninformed, in the sense of not reflecting changes in expected returns, a finding that is largely consistent with our earlier results showing that pension funds rebalance their portfolios in a *mechanical* fashion. Put simply, the short-term trades of pension funds reflect a passive strategy – set, for example, by asset-class weight limit restrictions specified in the investment mandate – rather than an active one that responds to changes in expected returns.

We complement the above analysis on price impact by examining cumulative returns around pension fund trades, similar to Dennis and Strickland (2002) and Coval and Stafford (2007). Figure 5 (CRET panels) shows a number of interesting results. First, pension funds tend to sell in response to positive cumulative returns over the preceding 12-months. They also tend to buy in response to falling returns over the preceding months; however, this effect is somewhat weaker. Thus, these findings provide further evidence on the rebalancing activity of pension funds, which complements our earlier results. Second, regardless of whether pension funds buy or sell, the trend observed in the pre-trade months continues, and eventually intensifies, during the actual trading month. This graphical representation is largely consistent with the earlier regression evidence showing that pension funds trade in the opposite direction to market movements. Third, the trend in cumulative abnormal returns attenuates or actually reverses in the months following the pension fund trades.

However, the effect of pension fund trades on financial markets will be genuinely stabilizing only if they move prices towards fundamentals (LSV, 1992; Coval and Stafford, 2007). We shed light on this issue by looking at the pattern of cumulative absolute abnormal returns (CAAR) in the months before and after pension fund trades. Abnormal returns are measured as the observed monthly returns minus the fitted returns resulting from regressing the returns on the same set of fundamental variables, $Z_{j,t}$, included in equation (12). Specifically, our hypothesis is that, if pension fund trades are stabilizing, then the deviation of market returns from their fundamental values in the months following their trades should be smaller than the deviation observed in the months preceding their trades. The results are clear-cut (see the CAAR panels in Figure 5): pension fund trades do not exert a stabilizing effect on prices. In fact, regardless of the asset class considered, their trades do not alter the slope of the CAAR curve, thereby indicating that the deviation of returns from their fundamental values is unaffected by pension funds' trading activity.

5 Pension Fund Performance

5.1 Investment Performance, Fund Characteristics and Herding Behavior

The analysis so far has largely concentrated on pension funds asset allocations. In this section, to complete the analysis, we turn to assess the funds' performance, in an attempt to link the performance of the funds to their characteristics, such as sector type, fund size, and fund asset allocation. We also examine to what extent funds' performance relates to the herding behavior of the funds.

To start with, we allocate funds to five portfolios according to their sample average performance. Table 7, Panel A, presents the annualized return associated with the five portfolios and the spread portfolio: *Low* denotes the lowest performing portfolio, *High* the highest performing portfolio, while the spread portfolio *H/L* is the difference between the *High* and *Low* portfolio returns. The *Low* and *High* portfolios generate average returns of 8.60% and 9.55% per annum, respectively. This implies that the *High* portfolio outperforms the *Low* portfolio by roughly 1% per annum, which, while strongly statistically significant, is economically quite small.

Next, we examine the characteristics of the constituents of the portfolios. Panel B.I shows that the best performing funds are private: they account for 71% of the funds in the *High* portfolio, and only 57% of the funds in the *Low* portfolio. The panel also shows an almost monotonic relationship between fund size and fund performance, with the best performing funds being four times larger than the worst performing funds.[25] We also find that the worst performing funds have a higher weighting in fixed-income and inflation-linked securities than the best performing funds (Panel B.II). Taken together, these findings show that the worst performing funds tend to be more mature than the best performing funds.

In Panel B.III, we present the average propensity of the constituents of each portfolio to follow their own trades ($\beta(p)^o$) and other funds' trades ($\beta(p)^h$). To compute the fund components for the individual funds, we employ the following steps. First, we exclude fund i from the sample, and compute the components $\beta(-i)_t^o$ and $\beta(-i)_t^h$ using eq. (4). We do the same for the remaining funds, which yields two matrices of components of dimension $T-1 \times N$ matrix, where T is the number of months and N is the number of funds. The two components associated with each fund are then computed as $\beta(i,t)^o{=}\beta_t^o - \beta(-i)_t^o$ and $\beta(i,t)^h{=}\beta_t^h - \beta(-i)_t^h$ where β_t^o and β_t^h are the cross-sectional averages of the individual fund measures $\beta(i,t)^o$ and $\beta(i,t)^h$, respectively. In this way, funds with high $\beta(i,t)^o$ display a strong tendency to follow their own trades, whereas funds with high value of $\beta(i,t)^h$ display a strong tendency to follow others' trades, *i.e.*, to herd. Similar to Table 2, we then compute the time-series averages ($\beta(i)^o$ and $\beta(i)^h$). By taking the averages of the constituents of each portfolio, we then obtain ($\beta(p)^o$) and ($\beta(p)^h$), displayed in Panel B.III. We find that the most profitable funds not only tend to follow more their own trades, but also they tend to herd less. This piece of evidence therefore suggests that herding might be a drag on the fund performance. However, this effect is economically small, possibly because all funds tend to display a strong tendency to herd.

[25]Note that Chen, Hong, Huang and Kubik (2004) instead document that larger funds face significant diseconomies of scale that limit their ability to move into and out of the more illiquid traded securities in size.

The above analysis did not condition on herding propensity, we therefore conduct the following portfolio-sort exercise. We sort the active funds every month into five portfolios by their tendency to herd, $\beta(i)_t^h = \beta_t^h - \beta(-i)_t^h$. Thus, the constituents of the *Low* (*High*) portfolio are the funds which display little (high) herding propensity. We repeat the analysis for the returns on the funds' total portfolios, as well as separately for the returns on the main asset classes (using the same sorting variable $\beta(i)_t^h$).

Panel A, Table 8, presents the average annualized returns associated with each of the portfolios and for the selected asset classes for the 1995-2012 period.[26] Although the funds that herd more tend to generate lower returns than the funds which herd less, these effects are economically small (30 basis points for the total portfolio) and statistically insignificant. Also the returns on the spread portfolios of the individual asset classes are not economically significant, and are statistically significant only for two asset classes (international equities and total bonds). Panel B shows that the findings are similar for the 'crisis period' 2008-2012.[27] Nevertheless, high-herding funds underperform low-herding funds by 85 basis points during this period, which is mainly driven by their allocations to international bonds.

In sum, there are small cross-sectional differences in the performance of pension funds, consistent with evidence that they have a strong tendency to herd. By engaging in herding activity, funds converge towards the performance of the peer-group fund. However, we also find that more mature and smaller funds generate lower returns than less mature and larger funds, respectively, which aligns closely with the evidence documented in Section 4.2.2 that pension funds herd in subgroups, defined by fund size and sponsor type.

5.2 Factors Driving Pension Fund Returns

Thus far, we have established that pension funds herd around the average fund, which generates the peer-group average return. A natural question then is: to what extent do the returns of the peer-group respond to changes in the returns of external benchmarks? More generally, what drives the returns of pension funds? To answer this question, we assess the responsiveness of pension fund peer-group benchmark returns (i.e., the returns of the average pension fund) to changes in external index returns and in liquidity conditions.

We examine peer-group returns by regressing the peer-group benchmark monthly return

[26] We find similar results for the 1987-2012 sample.

[27] The period of the global financial crisis and its aftermath.

($r_{t,j}^{PG}$) of asset j on the relevant market (i.e., external benchmark) return for asset class j ($Mkt_{j,t}$), as defined in Section 3.2, and our measure of liquidity (Liq_t):

$$r_{t,j}^{PG} = \alpha + \beta_1 Mkt_{j,t} + \beta_2 Mkt_{j,t-1} + \gamma_1 Liq_t + \gamma_2 Liq_{t-1} + \varepsilon_t. \tag{13}$$

Following Hu, Pan, and Wang (2013), given the high serial correlation in pension fund returns, we introduce lagged market and liquidity factors. As a result, estimates of the average (peer-group) pension fund's total exposure to the market and liquidity factors is given by, respectively, $\beta_1 + \beta_2$ (denoted $\Sigma\beta$) and $\gamma_1 + \gamma_2$ (denoted $\Sigma\gamma$). Panel A of Table 9 presents the estimates and shows that the explanatory power of this simple model is very high, except for cash/alternatives. We find that the exposure to market risk ($\Sigma\beta$) is close to unity for UK and international equities as well as for property. This will only be the case if the average pension fund holds the same securities with the same weights as the market index for each asset class. The coefficient on the market exposure for the three classes of bonds differs from unity. In the case of international bonds, the coefficient is 0.68, hence well below unity; the reason for this is that the average fund's weightings in its international bond portfolio differs significantly from the external index weightings.[28]

Turning to the liquidity factor, the average fund's allocation to international equities is significantly and positively exposed to changes in liquidity: increases in liquidity are associated with higher returns. The same holds for the two conventional bond portfolios, with the liquidity exposure of international bonds being roughly four times higher than that of domestic bonds. In contrast, the liquidity exposures are negative for UK index-linked bonds and for property returns. The regressions for the 'crisis period' 2008-12 are reported in Panel B. The results are broadly similar for market risk exposures although, not surprisingly, the liquidity exposures are generally larger in absolute size. In particular, the negative exposure of UK index-linked bond and property returns to the liquidity factor increased significantly during the crisis period.[29]

[28]There is a simple explanation for this. Market-weighted international bond indices will be dominated by the bonds of the most indebted and least credit worthy nations. No institutional investor will hold the market weighting in international bonds.

[29]Our measure of liquidity may not adequately reflect the underlying liquidity of the property market. The literature on measuring liquidity in the property market is rather scarce. One notable exception is Fisher, Geltner and Pollakowski (2007) who use a measure of demand pressure to capture property illiquidity. However, this measure is not available at monthly frequency. More importantly, when we include this measure in the principal component analysis at a quarterly frequency, we find that its loading on the first principal component has the opposite sign of the other variables. For all these reasons, we decided not to include any measure of illiquidity related to the property market.

6 Conclusions

Institutional investors are particularly large investors, tend to move in and out of asset classes at the same time and their net asset demands are often driven by factors other than risk-return considerations. Of particular interest are pension funds that globally are as large as mutual funds, but much less is known about their investment behavior. This is mainly due to the scarcity of available data to analyze. In this paper, we have access to a unique dataset on the UK pension funds' monthly allocations to major asset classes over the period 1987-2012. This dataset allows us to investigate the behavior of private- and public-sector funds over the past 25 years.

We find strong evidence that pension funds do indeed behave like lemmings as they herd strongly both in asset classes and in clearly defined subgroups. As a consequence, there are only small cross-sectional differences in the performance of pension funds. The fact that the subgroups are defined by fund size and sponsor type suggests that this herding behavior directly stems from the institutional structure of the pension fund industry, as well as the incentives pension funds have to watch closely their peer group. Specifically, we find that pension funds herd around the average fund (in their peer-group) in the very short term, and the average pension fund turns out to be a closet index matcher. We also find that pension funds rebalance their portfolios in a way that is consistent with meeting their mandate restrictions on asset weights in the short term, and with maintaining a long-term strategic asset allocation that matches the maturity of their liabilities. These two features – herding and mechanical portfolio rebalancing – are the key elements that characterize the asset allocation decisions of pension funds.

Our results also show that the trading activities of pension funds are consistent with the notion that they provide short-term liquidity to financial markets as they tend to trade in the opposite direction to market movements. However, this trading does not have an impact on asset prices that is persistent. Hence, we do not find evidence that pension funds have a stabilizing effect on financial markets, in the sense of moving asset prices closer to their fundamental values.

Overall, our findings have important implications for plan sponsors and policy makers responsible for financial stability: both of which would benefit from the design of an incentive structure that can better motivate pension funds to move away from 'short-termism' and focus on long-term returns and fundamental value. Indeed the investment decisions of pension funds are at the center of the active policy debate on the risks that the behavior of non-bank financial institutions pose for financial stability (Feroli, Kashyap, Schoenholtz and Shin, 2014; Haldane, 2014; Domanski, Shin and Sushko, 2015), and this paper adds to that debate by offering a deeper understanding of pension funds' traditional investment behavior.

A Appendix: A Closer Look at Herding in Subgroups

In this section, we describe the herding tests implemented in Section 4.2.2, where we group funds according to the sponsor type (private-sector and public-sector) and by size (small, medium and large).

Following Others by Size. We group funds into terciles according to their total assets. We do this for each month t, so that funds may migrate from one group to another as funds enter, or exit, the sample. We therefore end up with three groups of funds: small, medium and large. We measure small funds' average contribution from following small funds and the average contribution from following other medium and large funds. The average *same*-sector-type herding contribution for small funds at time t is given by the second term in eq. (4) limited to small funds averaged over the J asset classes:

$$\text{Avg same-size}_{\text{t}}^{\text{Small}} = \frac{1}{J}\sum_{j=1}^{J}\left[\sum_{n=1}^{S_{j,t}}\sum_{m=1,m\neq n}^{S^*_{j,t-1}}\left(\frac{D_{n,j,t}-\overline{RawW\Delta_t}}{S_{j,t}}\frac{D_{m,j,t-1}-\overline{RawW\Delta_{t-1}}}{S^*_{j,t-1}}\right)\right], \tag{A.1}$$

where $S_{j,t}$ is the number of small funds trading asset class j in month t; $S^*_{j,t-1}$ is the number of *other* small funds trading asset class j in month t; $D_{n,j,t}$ is a dummy variable that equals unity (zero) if pension fund n buys (sells) asset class j at time t; $D_{m,t}$ is a dummy variable that equals unity (zero) if pension fund m buys (sells) asset class j at time t. The average *different*-sector-type herding contribution for small funds at time t is given by the second term in eq. (4) limited to small funds following medium and large funds averaged over the J asset classes:

$$\text{Avg different-size}_{\text{t}}^{\text{Small}} = \frac{1}{J}\sum_{j=1}^{J}\left[\sum_{n=1}^{S_{j,t}}\sum_{m=1,m\neq n}^{ML_{j,t-1}}\left(\frac{D_{n,j,t}-\overline{RawW\Delta_t}}{S_{j,t}}\frac{D_{m,j,t-1}-\overline{RawW\Delta_{t-1}}}{ML_{j,t-1}}\right)\right], \tag{A.2}$$

where $ML_{j,t-1}$ is the number of medium and large funds trading asset class j in month $t-1$. All t-statistics are computed from time-series standard errors. The average *same*-size herding contribution for medium (large) funds is computed in a similar fashion to eq. (A.1), and the average *different*-size herding contribution for medium and large funds similar to eq. (A.2).

Following Others by Size and Type. We perform a 3×2 double sort in which we classify funds into terciles according to their size (small, medium, large) and sponsor type (private, public). The average *same*-size&type herding contribution for small private-sector funds at time t is given by the second term in eq. (4) limited to small private-sector funds averaged over the J asset classes:

$$\text{Avg same-size\&type}_{\text{t}}^{\text{Small Private}} =$$

$$= \frac{1}{J}\sum_{j=1}^{J}\left[\sum_{n=1}^{SC_{j,t}}\sum_{m=1,m\neq n}^{SC^{*}_{j,t-1}}\left(\frac{D_{n,j,t}-\overline{RawW\varDelta_t}}{SC_{j,t}}\frac{D_{m,j,t-1}-\overline{RawW\varDelta_{t-1}}}{SC^{*}_{j,t-1}}\right)\right], \tag{A.3}$$

where $SC_{j,t}$ is the number of small private-sector funds trading asset class j in month t; $SC^{*}_{j,t-1}$ is the number of *other* small private-sector funds trading asset class j in month t; $D_{n,j,t}$ is a dummy variable that equals unity (zero) if pension fund n buys (sells) asset class j at time t; $D_{m,t}$ is a dummy variable that equals unity (zero) if pension fund m buys (sells) asset class j at time t. The average *different*-size&type herding contribution for small private-sector funds at time t is given by:

$$\text{Avg different-size\&type}_{\text{t}}^{\text{Small Private}} =$$

$$= \frac{1}{J}\sum_{j=1}^{J}\left[\sum_{n=1}^{SC_{j,t}}\sum_{m=1,m\neq n}^{O_{j,t-1}}\left(\frac{D_{n,j,t}-\overline{RawW\varDelta_t}}{SC_{j,t}}\frac{D_{m,j,t-1}-\overline{RawW\varDelta_{t-1}}}{O_{j,t-1}}\right)\right], \tag{A.4}$$

where $O_{j,t-1}$ is the number of funds other than small private-sector funds (small public, medium public and private, and large public and private) trading asset class j in month $t-1$.

We then restrict the group of *other-different* by focusing on *other* funds of *different* type but the *same* size. The average *different*-type herding contribution for small private-sector funds at time t is given by:

$$\text{Avg different-type}_{\text{t}}^{\text{Small Private}} =$$

$$= \frac{1}{J}\sum_{j=1}^{J}\left[\sum_{n=1}^{SC_{j,t}}\sum_{m=1,m\neq n}^{SLA_{j,t-1}}\left(\frac{D_{n,j,t}-\overline{RawW\varDelta_t}}{SC_{j,t}}\frac{D_{m,j,t-1}-\overline{RawW\varDelta_{t-1}}}{SLA_{j,t-1}}\right)\right], \tag{A.5}$$

where $SLA_{j,t-1}$ is the number of other small public-sector funds trading asset class j in month $t-1$. Average contributions for small public, medium public and private, large public and private funds are computed using a similar method.

B Appendix: Measuring Liquidity

Our measure of liquidity consists of the first principal component of the negative of the change in the US TED spread, the negative of the change in the UK TED spread, the Pastor and Stambaugh (2003) measure of liquidity, the negative of the change in the VIX volatility index, and the negative of the change in the noise measure of Hu, Pan, and Wang (2013). We describe each measure in turn.

TED spread. The US TED spread is defined as the interest rate difference between 3-month eurodollar LIBOR and 3-month US Treasury bills. The UK TED spread is defined similarly using sterling equivalents. A large spread should be related to lower liquidity, reflecting among other things the willingness of banks to provide funding in the interbank market (Brunnermeier, 2009). We use the TED spread both for the US and the UK.

Pastor and Stambaugh liquidity measure. The Pastor and Stambaugh liquidity measure is constructed for the US stock market based on price reversals. Specifically, this measure focuses on an aspect of liquidity associated with temporary price fluctuations induced by order flows. The basic idea is that less liquid stocks are expected to experience more severe reversals in return for a given dollar value. We refer the reader to Pastor and Stambaugh (2003) for more details on the construction of the liquidity measure. However, it is worth noting here that in contrast to the other measures used, this is a measure of liquidity rather than illiquidity.

Chicago Board Options Exchange Market Volatility Index (VIX). VIX represents one measure of the market's expectation of stock market volatility over the next 30 day period. VIX is often referred to as the fear index. During episodes of risk panics, liquidity usually drops (Bacchetta, Tille and van Wincoop, 2012). Therefore, although VIX is not a 'pure' measure of illiquidity, it increases in periods of low liquidity, and may complement the information provided by the other measures used.

Hu, Pan and Wang (2013) noise measure. The noise measure is a market wide illiquidity measure that exploits the connection between the arbitrage capital in the market and observed price deviations in US Treasury bonds. It captures the noise in the yield curve, which can result, for example, from low value trades by hedge funds. Using the CRSP Daily Treasury database, the authors construct the noise measure by first backing out, day by day, a smooth zero-coupon yield curve, and then use this yield curve to price all available bonds on that day. Associated with each bond is the deviation of its market yield from the model yield. Aggregating the deviations across all bonds by calculating the root mean squared error, they obtain their noise measure. A large value of the noise measure should be related to lower liquidity. We refer the reader to Hu, Pan and Wang (2013) for more details on the construction of the noise measure.

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Table 1: Summary Statistics: UK Pension Fund Returns

Panel A: All Pension Funds	Mean	Med.	St.D.	Skew.	Kurt.	ρ_1	ρ_2	nobs
Total Assets	8.9	12.0	11.4	-1.13	7.55	0.11	-0.10	48030
Total Equities	9.4	13.6	15.5	-1.05	6.45	0.10	-0.12	47229
UK Equities	10.0	15.2	15.8	-0.95	6.81	0.09	-0.12	46847
Int. Equities	8.2	13.0	16.5	-0.83	4.97	0.10	-0.06	46175
Total Bonds	8.5	9.2	5.3	0.04	3.43	0.16	-0.04	44974
UK Bonds	8.8	8.9	5.8	0.01	3.41	0.13	-0.05	43744
Int. Bonds	7.5	5.6	6.3	1.20	8.40	0.14	-0.01	32257
UK IL	8.3	7.9	7.2	0.52	5.88	0.00	-0.18	34683
Cash/Alt.	5.6	5.0	1.1	0.56	3.38	0.87	0.86	47466
Property	7.1	7.8	3.4	-2.02	12.47	0.80	0.73	35676

Panel B: Private-Sector Funds (Corporates)	Mean	Med.	St.D.	Skew.	Kurt.	ρ_1	ρ_2	nobs
Total Assets	9.0	11.5	11.1	-1.12	7.53	0.11	-0.10	24808
Total Equities	9.5	13.9	15.5	-1.05	6.53	0.10	-0.12	24310
UK Equities	10.0	14.9	15.8	-0.95	6.82	0.09	-0.12	24048
Int. Equities	8.4	12.6	16.5	-0.85	5.11	0.10	-0.07	23471
Total Bonds	8.6	8.6	5.4	0.04	3.35	0.15	-0.05	22620
UK Bonds	8.8	9.0	5.8	0.00	3.40	0.13	-0.05	21949
Int. Bonds	7.7	6.1	6.5	0.93	6.30	0.15	-0.05	14165
UK IL	8.3	8.3	7.2	0.52	6.09	0.00	-0.18	17032
Cash/Alt.	5.5	5.1	1.1	0.62	3.24	0.86	0.85	24296
Property	7.1	7.3	3.4	-2.04	17.01	0.67	0.59	15889

Panel C: Public-Sector Funds (Local Authorities)	Mean	Med.	St.D.	Skew.	Kurt.	ρ_1	ρ_2	nobs
Total Assets	8.7	12.4	11.7	-1.15	7.56	0.11	-0.10	23222
Total Equities	9.4	13.7	15.5	-1.05	6.44	0.10	-0.12	22919
UK Equities	9.9	14.9	15.9	-0.94	6.81	0.09	-0.12	22799
Int. Equities	8.2	12.6	16.5	-0.84	4.95	0.10	-0.06	22704
Total Bonds	8.4	9.8	5.2	0.06	3.48	0.17	-0.02	22354
UK Bonds	8.8	9.1	5.8	0.04	3.33	0.14	-0.05	21795
Int. Bonds	7.6	5.2	6.4	1.23	8.65	0.15	0.05	18092
UK IL	8.2	7.9	7.1	0.54	5.70	0.01	-0.17	17651
Cash/Alt.	5.7	5.1	1.1	0.35	3.78	0.83	0.80	23170
Property	7.2	8.2	3.7	-1.89	10.49	0.82	0.75	19787

The table reports summary statistics on UK pension fund returns. For each month t, we take the cross-sectional mean of the available pension funds' annualized returns. We then report: the time series mean (Mean); median (Med.); standard deviation (St.D.); skewness (Skew.); kurtosis (Kurt.); the first- (ρ_1) and second-order (ρ_2) autocorrelation coefficients; and the number of observations (nobs). We present summary statistics for the following asset classes: total assets, total equities, UK equities, international equities, total bonds, UK bonds, international bonds, UK index-linked (UK IL) bonds, cash/alternatives and property. Panel A refers to the full sample of pension funds, whereas Panel B focuses on private-sector funds (i.e., corporates) and Panel C on public-sector funds (i.e., local authorities). The data cover a total of 108 corporate and 81 local authority pension funds over the period January 1987 - December 2012.

Table 2: Tests for Herding

Panel A: Cash Flows

	avg(β_t)	$\overline{\beta_t^o}$	$\overline{\beta_t^h}$	$\overline{\beta_t^h} - \overline{\beta_t^o}$
(1)	43.92	2.93	41.00	38.07
	[22.84]	[21.72]	[21.53]	[20.09]
(2)	47.17	3.59	43.58	39.99
	[23.56]	[20.95]	[21.98]	[20.21]

Panel B: Return-adjusted Weights

	avg(β_t)	$\overline{\beta_t^o}$	$\overline{\beta_t^h}$	$\overline{\beta_t^h} - \overline{\beta_t^o}$
(1)	55.11	2.57	52.54	49.97
	[30.43]	[20.71]	[28.76]	[26.99]
(2)	53.14	3.97	49.17	45.20
	[25.99]	[21.91]	[23.51]	[21.00]

The table reports in Panel A the sample average β_t resulting from estimating the regressions $\Delta_{j,t} = \beta_t \Delta_{j,t-1} + \varepsilon_{j,t}$, where $\Delta_{j,t}$ is the standardized raw fraction of institutions buying asset class j as defined in eq. (2) in Section 4. The t-statistics (reported in parentheses) are computed from time-series standard errors. The time t correlation β_t is then decomposed as $\beta_t = \rho\left(\Delta_{j,t}, \Delta_{j,t-1}\right) = \beta_t^o + \beta_t^h$, as in eq. (4), where β_t^o indicates pension funds 'following their own trades' into and out of the same asset class, and β_t^h indicates pension funds 'following others' (herding). We report the sample average $\overline{\beta_t^o}$ and $\overline{\beta_t^h}$ with the associated time-series t-statistics in parentheses. Specification (1) includes the seven asset classes: UK equities, international equities, UK bonds, international bonds, UK index-linked bonds, cash/alternatives and property. Specification (2) excludes cash/alternatives, focusing on the remaining six asset classes. In Panel B, we repeat the analysis by replacing the demand measure based on cash flows with the demand measure based on return adjusted-weights ($\widetilde{\Delta_{j,t}}$); we identify pension fund n as a buyer (seller) of asset class j, if the return-adjusted portfolio weight of asset class j increased (decreased), i.e., the flow differential $ncf_{n,j,t} - ncf_{n,p,t}$ is positive (negative). The data cover the period January 1987 - December 2012.

Table 3: Herding in Subgroups Defined by Fund Size and Sponsor Type: Single Sort

Panel A: Following Others by Sponsor Type

	(1) All Assets			(2) All Assets ex CA		
	Same	Other	Diff.	Same	Other	Diff.
Private	0.52	0.42	0.10	0.57	0.28	0.30
Funds	[19.76]	[10.12]	[3.06]	[21.16]	[6.58]	[8.07]
Public	1.24	0.43	0.81	1.04	0.28	0.77
Funds	[24.59]	[9.96]	[18.68]	[20.60]	[6.49]	[17.70]

Panel B: Following Others by Fund Size

	(1) All Assets			(2) All Assets ex CA		
	Same	Other	Diff.	Same	Other	Diff.
Small	1.02	0.73	0.29	0.90	0.61	0.29
Funds	[19.88]	[18.08]	[7.56]	[16.85]	[15.54]	[7.24]
Medium	0.92	0.70	0.22	0.75	0.57	0.18
Funds	[16.63]	[17.14]	[6.27]	[14.41]	[14.07]	[5.43]
Large	0.64	0.50	0.15	0.66	0.38	0.29
Funds	[18.37]	[12.58]	[4.39]	[17.80]	[9.40]	[7.51]

The table reports the decomposition of a measure of herding whereby pension funds 'following others' is decomposed into pension funds following others of the *Same* type and *Other* type. The analysis is based on the standardized fraction of pension funds increasing/decreasing the return-adjusted weight in asset j in month t ($\widetilde{\Delta}_{j,t}$). *Same* refers to the average contribution to the correlation from each pension fund following other pension funds with the same characteristics, see eq. (7). *Other* refers to the average contribution to the correlation from each pension fund following other pension funds with different characteristics, see eq. (8). Numbers are reported in percent. Panel A focuses on the sponsor type, private-sector funds (i.e., those sponsored by corporates) vs. public-sector funds (i.e., those sponsored by local authorities). Panel B focuses on the size differences, whereby funds are sorted into small, medium and large in each period t. (1) All Assets includes the seven asset classes: UK equities, international equities, UK bonds, international bonds, UK index-linked bonds, cash/alternatives and property. (2) All Assets ex CA excludes cash/alternatives, focusing on the remaining six asset classes. All t-statistics (reported in parentheses) are computed from time-series standard errors.

Table 4: Herding in Subgroups Defined by Fund Size and Sponsor Type: Double Sort

Panel A: All Assets

	Private Funds			Public Funds		
	Same	Other	Diff.	Same	Other	Diff.
Small	0.80	1.04	−0.24	1.40	1.01	0.39
Funds	[15.00]	[14.01]	[−3.59]	[15.49]	[12.91]	[4.48]
Medium	0.55	0.46	0.09	1.27	0.45	0.82
Funds	[6.49]	[5.78]	[0.91]	[19.48]	[5.80]	[9.98]
Large	1.09	0.17	0.93	0.99	0.26	0.73
Funds	[21.92]	[3.02]	[13.68]	[17.22]	[4.56]	[11.35]

Panel B: All Assets ex CA

	Private Funds			Public Funds		
	Same	Other	Diff.	Same	Other	Diff.
Small	0.70	0.90	−0.20	1.29	0.84	0.45
Funds	[12.63]	[11.54]	[−2.91]	[13.79]	[10.69]	[5.14]
Medium	0.58	0.32	0.26	1.05	0.28	0.77
Funds	[6.39]	[4.30]	[2.55]	[16.80]	[3.79]	[9.31]
Large	1.42	0.10	1.31	0.80	0.17	0.64
Funds	[22.72]	[1.81]	[16.23]	[14.43]	[2.75]	[9.48]

The table reports the decomposition of a measure of herding whereby pension funds 'following others' is decomposed into pension funds following others of the *Same* type and *Other* type, controlling for size. The analysis is based on the standardized fraction of pension funds increasing/decreasing the return-adjusted weight in asset j in month t ($\widetilde{\Delta}_{j,t}$). Funds are sorted according to their size and then for each tercile into private- and public-sector. *Same* refers to the average contribution to the correlation from each pension fund following other pension funds of the *same size and sponsor type*, see eq. (A.3). *Other* refers to the average contribution to the correlation from each pension fund following other pension funds of the *same size but different sponsor type*, see eq. (A.5). Numbers are reported in percent. Panel A includes the seven asset classes: UK equities, international equities, UK bonds, international bonds, UK index-linked bonds, cash/alternatives and property. Panel B excludes cash/alternatives (ex CA), focusing on the remaining six asset classes. All t-statistics (reported in parentheses) are computed from time-series standard errors.

Table 5: Evolution of Portfolio Weights

Panel A: 1995-2012	Tot.Eq.	UK Eq.	Int.Eq.	Tot.Bo.	UK Bo.	Int.Bo.	UK IL	CA	Prop.
$\Delta \log(\omega_{jt})$	-1.70	-3.56	0.37	5.06	6.16	2.71	1.28	4.43	2.24
$r_{jt} - r_{pt}$	0.41	0.64	0.00	-0.28	-0.05	-0.84	0.13	-2.50	-0.19
$ncf_{jt} - ncf_{pt}$	-2.11	-4.20	0.38	5.34	6.21	3.55	1.14	6.93	2.43
Corr(r,ncf)	-0.32	-0.33	-0.10	-0.25	-0.18	-0.22	-0.16	-0.20	-0.04
% Ex.Var(r)	83.3	76.66	91.01	70.41	72.9	38.32	84.52	38.43	95.42
% Ex.Cov(r,ncf)	12.24	15.78	4.23	15.77	11.8	18.14	8.05	16.85	1.53
% Ex.Var(ncf)	4.47	7.55	4.76	13.83	15.3	43.54	7.43	44.72	3.05

Panel B: 2008-2012	Tot.Eq.	UK Eq.	Int.Eq.	Tot.Bo.	UK Bo.	Int.Bo.	UK IL	CA	Prop.
$\Delta \log(\omega_{jt})$	-1.52	-4.39	-0.23	1.4	1.33	0.57	0.71	4.63	-0.13
$r_{jt} - r_{pt}$	0.5	0.65	0.73	2.82	2.58	3.57	3.04	-3.2	-5.71
$ncf_{jt} - ncf_{pt}$	-2.03	-5.04	-0.96	-1.42	-1.25	-3.00	-2.33	7.83	5.58
Corr(r,ncf)	-0.4	-0.38	-0.21	-0.42	-0.41	-0.30	-0.19	-0.54	0.18
% Ex.Var(r)	84.71	78.2	89.51	74.48	76.25	44.18	85.81	48.52	92.11
% Ex.Cov(r,ncf)	12.41	16.16	7.24	18.79	17.74	22.94	8.40	32.51	5.39
% Ex.Var(ncf)	2.88	5.64	3.25	6.73	6.01	32.88	5.80	18.97	2.50

The table reports the mean (annualized) percentage change in the average pension fund's portfolio weights, $\Delta \log(\omega_{j,t})$, and its decomposition into the return differential across assets classes, $(r_{j,t} - r_{p,t})$, and shifts in net cash flows across asset classes, $(ncf_{j,t} - ncf_{p,t})$. $\Delta\log(\omega_{j,t}) \simeq (r_{j,t} - r_{p,t}) + (ncf_{j,t} - ncf_{p,t})$, where $r_{j,t}$ is the value-weighted rate of return on UK pension funds' holdings of asset class j; $ncf_{j,t}$ is the rate of net cash flow into that asset class during month t; $r_{p,t}$ is the value-weighted return of the total portfolio during month t; and $ncf_{p,t}$ is the net cash flow into the total portfolio during month t. Associated with this is the variance decomposition $\text{var}(\Delta\log(\omega_{j,t})) \simeq \text{var}(r_{j,t} - r_{p,t}) + \text{var}(ncf_{j,t} - ncf_{p,t}) + 2\text{cov}(r_{j,t} - r_{p,t}, ncf_{j,t} - ncf_{p,t})$. We report the monthly variance of changes in portfolio weights due to the variance of return differentials, var(r), the variance of net cash flow differentials, var(ncf), and the covariance between these, cov(r,ncf) (expressed in percentages). Results for the period from January 1995 to December 2012 are reported in Panel A, while those for the global financial crisis and its aftermath from January 2008 to December 2012 are reported in Panel B. 'CA' refers to cash/alternatives and 'UK IL' refers to UK index-linked bonds.

Table 6: Regressions of Net Cash Flows on Asset Market Returns and Liquidity

Panel A: Sample 1995-2012

	α	β_1	β_2	β_3	β_4	γ_1	γ_2	γ_3	γ_4	$\Sigma\beta$	$\Sigma\gamma$	R^2
UK Eq.	-0.28^a	-0.04^a	-0.03^a	-0.01	-0.02^a	-0.02	0.01	-0.01	0.06^b	-0.11^a	0.04	19.74
Int. Eq.	0.08^c	-0.01	-0.04^a	-0.03^a	-0.03^a	-0.01	-0.00	0.05^b	0.07^a	-0.11^a	0.11^b	19.67
UK Bo.	0.71^a	-0.14^b	-0.15^b	-0.10^b	0.08	0.01	0.16^a	0.14^b	-0.10	-0.31^b	0.22	8.17
Int. Bo.	0.64^a	-0.35^a	-0.21^a	-0.13^c	0.01	-0.19	-0.04	-0.33^b	-0.07	-0.68^a	-0.63^c	6.21
UKIL	0.23^b	0.01	-0.11^b	-0.06^c	-0.06	0.06	0.06	0.08^c	0.01	-0.22^b	0.21	5.31
CA	0.60^b	12.81^b	-5.09	7.31	-14.88^b	0.43^a	-0.00	-0.00	-0.11	0.16	0.31	4.69
Prop.	0.13^a	0.05	0.05	0.06	-0.04	0.01	-0.02	-0.01	0.01	0.12^a	-0.01	4.10

Panel B: Sample 2008-2012

	α	β_1	β_2	β_3	β_4	γ_1	γ_2	γ_3	γ_4	$\Sigma\beta$	$\Sigma\gamma$	R^2
UK Eq.	-0.38^a	-0.05^a	-0.06^a	-0.01	-0.05^a	-0.03	0.05	-0.02	0.12^a	-0.17^a	0.12	39.67
Int. Eq.	-0.05	-0.02^c	-0.06^a	-0.01	-0.03^a	0.00	0.02	0.02	0.07^a	-0.13^a	0.11^c	34.94
UK Bo.	0.06	-0.18^a	-0.08	-0.05	0.01	0.04	0.14^a	0.06^b	0.05^c	-0.30^b	0.29^a	36.47
Int. Bo.	0.07	-0.32^a	-0.11	-0.02	-0.06	-0.13	0.09	-0.18	0.11	-0.51^a	-0.12	16.68
UKIL	-0.20	0.01	-0.01	0.01	-0.03	0.07	0.05	0.05	-0.02	-0.02	0.15	-1.45
CA	0.70^a	3.01	-1.18	5.75	-7.57	0.31^a	0.19	-0.08	-0.09	0.01	0.33^b	21.60
Prop.	0.46^a	0.20^a	0.05	0.06	-0.05	0.00	-0.04^b	-0.03	-0.03	0.26^a	-0.10^b	46.04

The table reports regressions of changes in aggregate portfolio weights due to the net cash flow rate differential component $ncf_{j,t}$ -$ncf_{p,t}$, denoted by $\widetilde{NCF}_{j,t}$, on current and past asset market returns and liquidity effects. Specifically, we estimate $\widetilde{NCF}_{j,t} = \alpha + \sum_{s=0}^{3} \beta_s Mkt_{j,t-s} + \sum_{s=0}^{3} \gamma_s Liq_{t-s} + \varepsilon_t$. $Mkt_{j,t}$ is the time-t return on the relevant external benchmark for asset class j. The measure of liquidity Liq_t is the first principal component of the negative of the change in the US TED spread, the negative of the change in the UK TED spread, the Pastor and Stambaugh (2003) measure of liquidity, the negative of the change in the VIX volatility index, and the negative of the change in the noise measure of Hu, Pan, and Wang (2013). $\Sigma\beta$ ($\Sigma\gamma$) denotes the sum of contemporaneous and lagged betas (gammas). The regression is at a monthly frequency for the period from January 1995 to December 2012 in Panel A, and for the global financial crisis and its aftermath from January 2008 to December 2012 in Panel B. R^2s denote the adjusted R-squared. t-statistics are computed by using Newey-West standard errors. a, b, and c denote the 1-, 5-, and 10-percent significance levels, respectively. α is the constant term in the regression, *CA* refers to cash/alternatives and *UK IL* refers to UK index-linked bonds.

Table 7: Fund Performance and Characteristics

Panel A: Portfolio Performance						
	Low	2	3	4	High	H/L
Ret. (%)	8.61	8.63	8.83	8.99	9.55	0.98
p-value	(0.002)	(0.002)	(0.001)	(0.001)	(0.000)	(0.000)

Panel B: Portfolio Characteristics						
	B.I Sector and Size					
Private (%)	56.5	39.3	36.8	50.5	71.2	14.8
Public (%)	43.5	60.7	63.2	49.5	28.8	-14.8
Size (bn)	0.4	0.8	1.2	1.2	1.6	1.2
	B.II Portfolio Weights					
Equities	65.2	68.1	69.2	67.9	66.0	0.8
UK Eq.	41.3	43.8	43.4	42.1	41.3	0.0
Int. Eq.	23.9	24.3	25.8	25.8	24.7	0.8
Bonds	16.4	14.9	12.7	12.9	12.6	-3.8
UK Bo.	11.4	11.3	9.3	9.2	8.9	-2.5
Int. Bo.	5.0	3.6	3.4	3.7	3.7	-1.3
UK IL	14.0	7.4	7.6	7.3	7.5	-6.6
	B.III Herding Components					
$\beta(p)^o$	-0.01	-0.02	-0.02	-0.03	0.11	0.1
$\beta(p)^h$	0.00	0.04	0.05	0.00	-0.07	-0.1

This table presents in Panel A the performance results from allocating funds into five portfolios according to their sample average performance. *Low* denotes the low performance portfolio, while *High* the high performance portfolio; the spread portfolio *H/L* is the difference between the *High* and *Low* portfolio returns. p-values are reported in parentheses. Panel B presents the characteristics of the constituents of the portfolios. In Panel B.I, *Private* (*Public*) denotes the percentage of *Private* (*Public*) funds in the selected portfolio; *Size* denotes the average fund size (in billions of pounds) in the selected portfolio. Panel B.III presents the average propensity of the constituents of each portfolio to follow their own trades ($\beta(p)^o$) and other funds' trades ($\beta(p)^h$). To compute the fund components for the individual funds, we employ the following steps. First, we exclude fund i from the sample, and compute the components $\beta(-i)^o_t$ and $\beta(-i)^h_t$ using eq. (4). We do the same for the remaining funds, which yields two matrices of components of dimension $T-1 \times N$ matrix, where T is the number of months and N is the number of funds. The two components associated with each fund are then computed as $\beta(i,t)^o{=}\beta^o_t - \beta(-i)^o_t$ and $\beta(i,t)^h{=}\beta^h_t - \beta(-i)^h_t$ where β^o_t and β^h_t are the cross-sectional averages of the individual fund measures $\beta(i,t)^o$ and $\beta(i,t)^h$, respectively. In this way, funds with high $\beta(i,t)^o$ display a strong tendency to follow their own trades, whereas funds with high value of $\beta(i,t)^h$ display a strong tendency to follow others' trades, *i.e.*, to herd. Similar to Table 2, we then compute the time-series averages ($\beta(i)^o$ and $\beta(i)^h$). By taking the averages of the constituents of each portfolio, we then obtain ($\beta(p)^o$) and ($\beta(p)^h$). The data cover a total of 108 corporate and 81 local authority pension funds over the period February 1987 - December 2012.

Table 8: Portfolio Returns: Single Sorts on Herding

Panel A: Sample 1995-2012

	Portfolios					
	Low	2	3	4	High	H/L
Tot. Assets	7.69^a	7.72^a	7.71^a	7.72^a	7.43^a	-0.26
Equities	8.18^b	8.03^b	8.18^b	8.23^b	8.04^b	-0.14
UK	8.47^b	8.31^b	8.47^b	8.50^b	8.49^b	0.02
Int.	7.74^b	7.48^c	7.66^c	7.71^b	7.41^c	-0.33^c
Bonds	7.59^a	7.39^a	7.38^a	7.44^a	7.24^a	-0.35^c
UK	7.78^a	7.87^a	7.80^a	7.79^a	7.68^a	-0.11
Int.	7.27^a	6.10^a	5.97^a	6.20^a	6.50^a	-0.77
UK IL	8.06^a	8.26^a	7.89^a	7.91^a	8.04^a	-0.02

Panel B: Sample 2008-2012

	Portfolios					
	Low	2	3	4	High	H/L
Tot. Assets	4.79	4.82	4.83	4.38	3.95	-0.85^c
Equities	4.53	4.26	4.25	4.27	4.06	-0.47
UK	4.65	4.50	4.42	4.25	4.35	-0.29
Int.	4.83	4.53	4.47	4.85	4.24	-0.60
Bonds	8.24^a	8.09^a	7.99^a	7.91^a	7.75^a	-0.49
UK	7.69^a	7.86^a	8.01^a	7.89^a	7.42^b	-0.27
Int.	11.23^a	8.35^c	6.87	7.76^c	8.39^b	-2.84
UK IL	8.69^b	8.77^b	8.09^c	8.22^b	8.34^c	-0.35

This table presents the portfolio returns obtained by allocating the funds to five portfolios according to the herding component $\beta(i)^h_t$. To obtain this measure, we do the following: first, we compute the herding measure, i.e. the follow others' component, by excluding fund i from the analysis. By doing this, we obtain for fund i the time-series $\beta(-i)^h_t$. We do the same for the remaining funds, which results in a $T-1 \times N$ matrix, whereby T is the number of months and N is the number of funds. Then, the fund i's herding measure, our sorting variable, is given by $\beta(i)^h_t{=}\beta^h_t - \beta(-i)^h_t$ where β^h_t is the cross-sectional average of the individual funds' measures $\beta(-i)^h_t$. Note that when a fund that tends to display a high (low) propensity to herd is excluded, the measure $\beta(-i)^h_t$ is low (high). For this reason, high values of $\beta(i)^h_t$ are instead associated with funds that display a high tendency to herd, i.e. follow others' trades. Thus, the *Low* portfolio contains the funds which display low herding behavior, whereas the *High* portfolio contains the funds which display high herding behavior. The spread portfolio is the difference between the *High* and the *Low* portfolio returns. Portfolios are constructed at a monthly frequency. The data cover a total of 108 corporate and 81 local authority pension funds. Panel A shows the results for the period January 1995 - December 2012, whereas Panel B shows the results for the crisis period January 2008 - December 2012. a, b, and c denote the 1-, 5-, and 10-percent significance levels, respectively.

Table 9: Regressions of Peer-Group Benchmark Returns on Market Returns and Liquidity

Panel A: Sample 1995-2012

	α	β_1	β_2	γ_1	γ_2	$\Sigma\beta$	$\Sigma\gamma$	R^2
UK Eq.	0.10^a	0.98^a	0.00	-0.02	0.01	0.98^a	-0.01	99.75
Int. Eq.	0.10	0.96^a	0.04^b	0.15^a	0.03	1.00^a	0.18^a	96.32
UK Bo.	-0.04	1.10^a	0.05^b	0.06^a	0.07^a	1.15^a	0.13^a	96.52
Int. Bo.	0.27^a	0.70^a	-0.02	0.36^a	0.20^a	0.68^a	0.57^a	80.78
UK IL	-0.00	1.10^a	-0.01	0.00	-0.05^a	1.09^a	-0.05^b	98.07
CA	0.21	1.75	-0.92	0.13^b	-0.01	0.83^b	0.11	5.50
Prop.	-0.02	1.27^a	-0.22	-0.05	-0.15^c	1.04^a	-0.20^b	72.40

Panel B: Sample 2008-2012

	α	β_1	β_2	γ_1	γ_2	$\Sigma\beta$	$\Sigma\gamma$	R^2
UK Eq.	0.14^a	0.97^a	0.00	-0.03^c	0.02	0.98^a	-0.02	99.82
Int. Eq.	0.04	0.95^a	0.02	0.20^a	0.01	0.97^a	0.20^a	98.84
UK Bo.	-0.02	1.12^a	0.06	0.08^b	0.11^a	1.17^a	0.18^a	94.18
Int. Bo.	0.39^a	0.55^a	-0.00	0.44^a	0.17^a	0.54^a	0.60^a	79.19
UK IL	0.04	1.17^a	0.01	-0.01	-0.11^a	1.18^a	-0.12^a	97.63
CA	0.31^c	4.77	-4.96	0.14	-0.04	-0.20	0.10	-2.11
Prop.	-0.08	1.61^a	-0.53^a	0.02	-0.32^a	1.08^a	-0.30^a	79.38

The table reports regressions of the peer-group benchmark monthly return ($r^{PG}_{j,t}$) of asset j on the relevant (external benchmark) market return for asset class j and liquidity. Specifically, we estimate $r^{PG}_{j,t} = \alpha + \beta_1 Mkt_{j,t} + \beta_2 Mkt_{j,t-1} + \gamma_1 Liq_t + \gamma_2 Liq_{t-1} + \varepsilon_t$. $Mkt_{j,t}$ is the time-t return of the relevant external benchmark for asset class j. The measure of liquidity Liq_t is the first principal component of the negative of the change in the US TED spread, the negative of the change in the UK TED spread, the Pastor and Stambaugh (2003) measure of liquidity, the negative of the change in the VIX volatility index, and the negative of the change in the noise measure of Hu, Pan, and Wang (2013). $\Sigma\beta$ ($\Sigma\gamma$) denotes the sum of contemporaneous and lagged betas (gammas) with the associated t-statistics beneath. The regression is at a monthly frequency for the period from January 1995 to December 2012 in Panel A, and for the 'crisis period' from January 2008 to December 2012 in Panel B. R^2s denote the adjusted R-squareds. t-statistics are computed by using the Newey-West standard errors. a, b, and c denote the 1-, 5-, and 10-percent significance levels, respectively. α is the constant term in the regression, 'CA' refers to cash/alternatives and 'UK IL' refers to UK index-linked bonds.

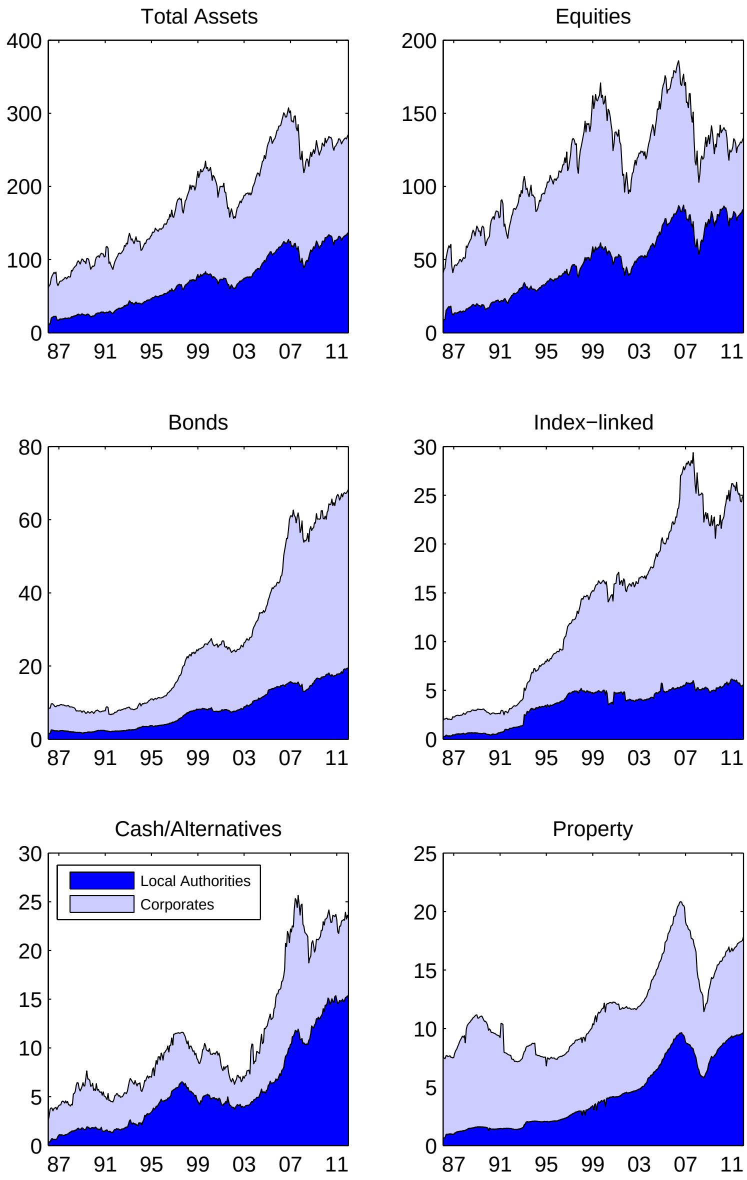


Figure 1: UK Pension Fund Asset Holdings by Sponsor Type (in Billion Pounds)

Note: The figure shows UK private- and public-sector funds' total asset holdings as well as their holdings in equities, bonds, UK inflation-linked bonds, cash/alternatives and property for the period from January 1987 to December 2012.

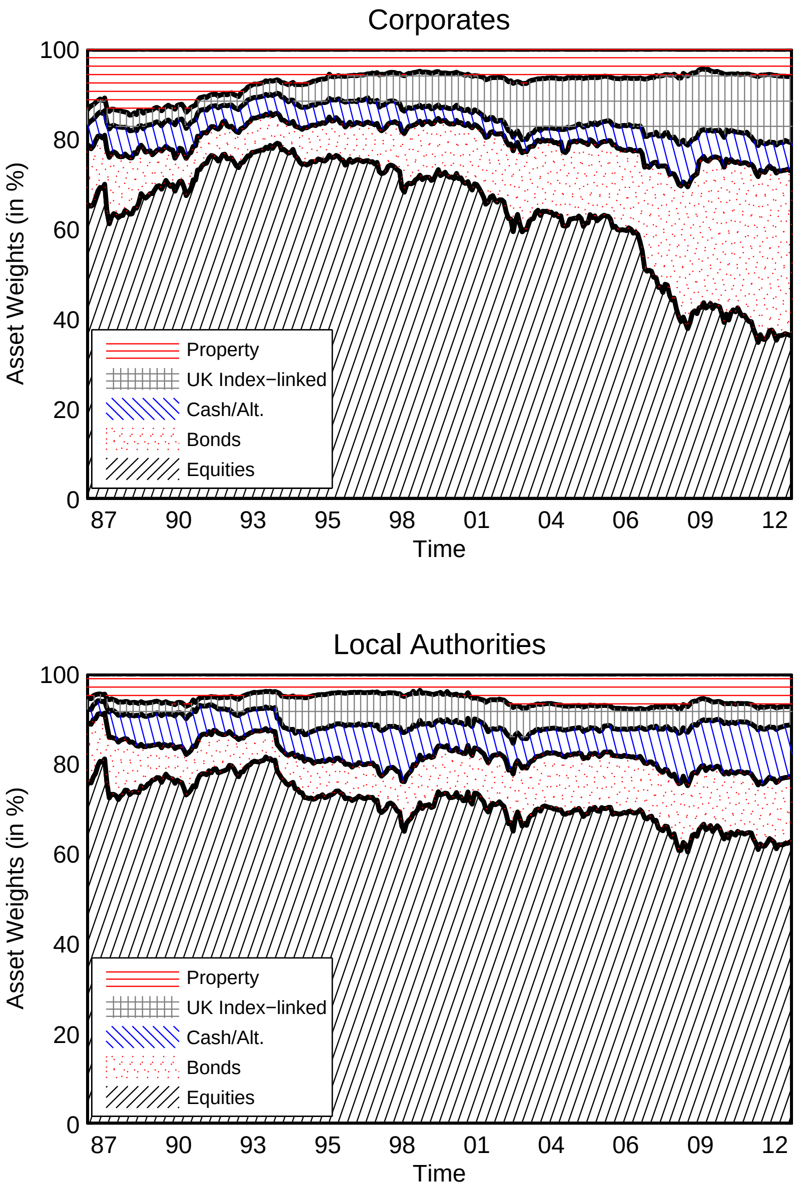


Figure 2: Asset Weights by Sponsor Type (in %)

Note: The figure shows UK private- and public-sector funds' asset allocation weightings in equities, bonds, UK inflation-linked bonds, cash/alternatives and property for the period from January 1987 to December 2012.

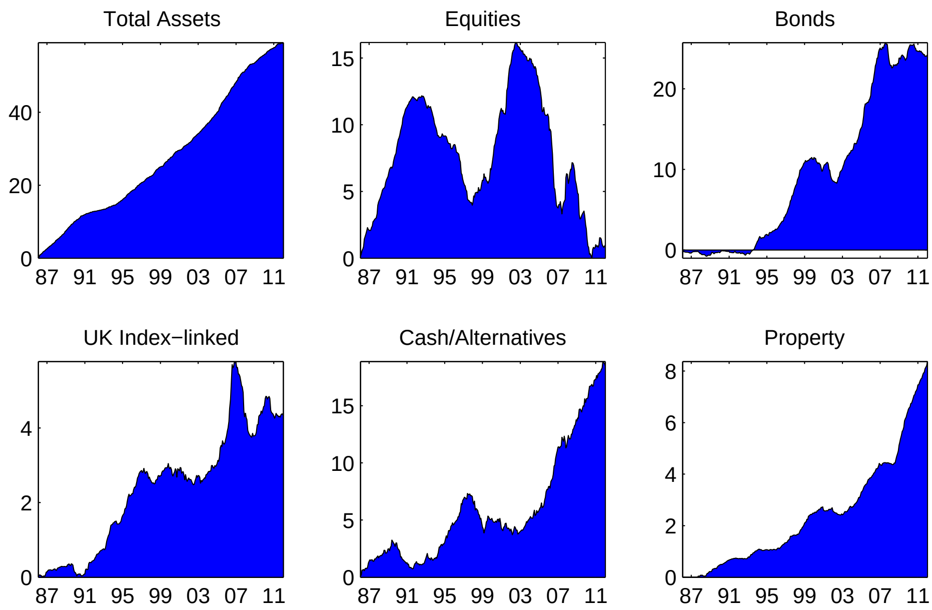


Figure 3: Cumulative Net Cash Flows by UK Pension Funds (in Billion Pounds)

Note: The figure shows UK pension funds cumulative net cash flows (net investment) in total assets and in equities, bonds, UK index-linked bonds, cash/alternatives and property for the period from January 1987 to December 2012.

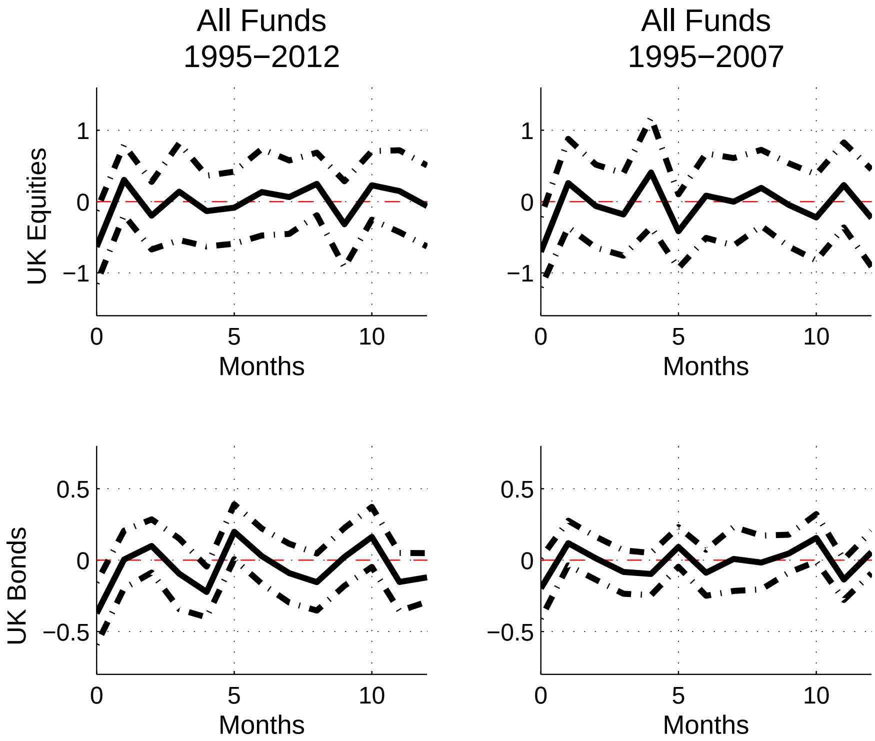


Figure 4: Price Impact

Note: The figure shows the price impact of pension fund trades on UK equities and bonds. We use the returns on the external benchmark indices described in Section 3.2. Specifically, we organize our analysis around the following regression:

$$r_{j,t+h} = \gamma_{j,0} + \gamma_{j,1} CF_{j,t} + \gamma_{j,2} Z_{j,t} + \epsilon_{j,t}$$

and plot $\gamma_{j,1}$ for h=0,...,12 (solid line) together with 95% confidence intervals (dot-dashed line), calculated using Newey-West standard errors. The set of control variables for UK equities include: lagged equity returns (to allow for momentum); dividend yields; term spreads (the 10- minus the 2-year nominal gilt rates); and, realized equity return volatility (the sum of squared daily equity returns). The set of control variables for UK bonds include lagged bond returns; term spreads; the short rate (the 3-month interbank rate); five-year break-even inflation rate (the difference between the 5-year nominal and real rates); and, realized bond return volatility (the sum of squared daily bond returns). Left panels show the results for the 1995-2012 sample period, whereas right panels exclude the 2008-12 crisis period. *Source*: Datastream, Bank of England and authors' calculations.

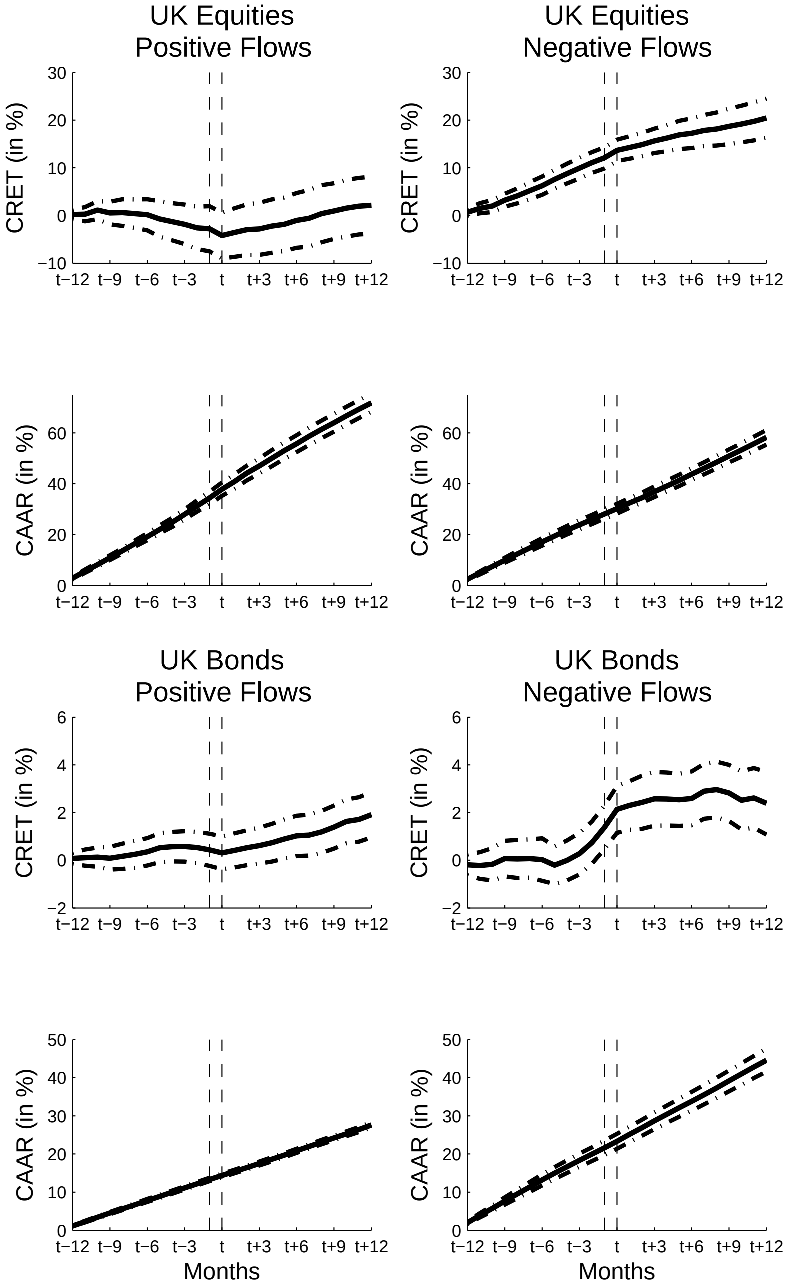


Figure 5: Cumulative Returns Around Pension Fund Trades

Note: The figure shows the average monthly cumulative returns (CRET) and the average monthly cumulative abnormal returns (CAAR) for a window of 24-months around pension fund trades. The CAAR are measured as the monthly returns minus the fitted returns resulting from the regression of the returns on a set of fundamental variables. The regression is estimated over a rolling window of five years. The set of control variables for UK equities comprise: lagged equity returns (to allow for momentum); dividend yields; term spreads (the 10- minus the 2-year nominal gilt rate); and, realized equity return volatility (sum of squared daily equity returns). The set of control variables for UK bonds comprise: lagged bond returns; term spreads; the short rate (the 3-month interbank rate); five-year break-even inflation rates (the difference between the 5-year nominal and real rates); and, realized bond return volatility. Each month, the average (abnormal) returns (solid line) is calculated, and then the time-series mean and standard error of the mean are used to compute the 95% confidence intervals (dot-dashed lines). The vertical dotted lines delimit the month in which pension funds traded. Left panels refer to positive flows and right panels depict negative flows. The sample period goes from January 1995 to December 2012.

Internet Appendix (not for publication)

The Market for Lemmings: The Herding Behaviour of Pension Funds

by

David Blake, Lucio Sarno and Gabriele Zinna

Table of Content Internet Appendix

A.I Summary Statistics, Herding and Portfolio Rebalancing

Table A1: Summary Statistics: Peer-group Benchmark Returns

Panel A: All Pension Funds							
	Mean	Med.	St.D.	Skew.	Kurt.	ρ_1	ρ_2
Total Assets	8.9	12.0	10.9	-1.2	7.7	0.1	-0.1
Total Equities	9.5	13.2	15.5	-1.1	6.5	0.1	-0.1
UK Equities	9.9	15.6	15.7	-1.0	6.9	0.1	-0.1
Int. Equities	8.3	13.2	16.4	-0.8	4.9	0.1	-0.1
Total Bonds	8.6	9.6	5.5	0.1	3.6	0.2	0.0
UK Bonds	8.9	8.4	5.9	0.0	3.4	0.1	-0.1
Int. Bonds	7.8	7.2	6.3	0.8	5.6	0.1	0.0
UK IL	8.4	8.4	7.2	0.6	5.7	0.0	-0.2
Cash/Alt.	7.2	7.2	2.5	-0.8	6.2	0.2	0.1
Property	8.1	8.4	4.7	-1.3	15.9	0.5	0.5
Panel B: Private-Sector Funds (Corporates)							
	Mean	Med.	St.D.	Skew.	Kurt.	ρ_1	ρ_2
Total Assets	9.0	12.0	10.8	-1.2	8.0	0.1	-0.1
Total Equities	9.4	13.2	15.5	-1.1	6.5	0.1	-0.1
UK Equities	9.9	15.6	15.7	-1.0	7.0	0.1	-0.1
Int. Equities	8.3	13.2	16.4	-0.8	4.9	0.1	-0.1
Total Bonds	8.6	9.6	5.5	0.1	3.6	0.1	-0.1
UK Bonds	8.9	8.4	6.0	0.0	3.4	0.1	-0.1
Int. Bonds	8.0	7.2	6.3	0.8	5.5	0.1	0.0
UK IL	8.3	8.4	7.2	0.6	5.7	0.0	-0.2
Cash/Alt.	7.4	7.2	2.8	-0.7	6.7	0.1	0.0
Property	8.1	7.2	4.9	-1.3	18.4	0.4	0.4
Panel C: Public-Sector Funds (Local Authorities)							
	Mean	Med.	St.D.	Skew.	Kurt.	ρ_1	ρ_2
Total Assets	8.8	12.0	11.4	-1.2	7.6	0.1	-0.1
Total Equities	9.5	14.4	15.5	-1.0	6.4	0.1	-0.1
UK Equities	9.9	15.6	15.8	-0.9	6.8	0.1	-0.1
Int. Equities	8.5	13.2	16.4	-0.8	4.8	0.1	-0.1
Total Bonds	8.4	9.6	5.2	0.1	3.5	0.2	0.0
UK Bonds	8.7	8.4	5.8	0.0	3.4	0.2	0.0
Int. Bonds	7.5	6.0	6.1	0.8	5.8	0.1	0.0
Index-linked	8.2	8.4	7.0	0.5	5.7	0.0	-0.2
Cash/Alt.	6.3	7.2	1.8	-0.8	5.8	0.4	0.3
Property	8.0	8.4	4.3	-1.5	11.9	0.7	0.6

The table reports summary statistics of pension fund peer-group benchmark returns. We report: the time series mean (Mean); median (Med.); standard deviation (St.D.); skewness (Skew.); kurtosis (Kurt.); the first- (ρ_1) and second-order (ρ_2) autocorrelation coefficients; and the number of observations (nobs). We present summary statistics for the following asset classes: total assets, total equities, UK equities, international equities, total bonds, UK bonds, international bonds, UK index-linked (UK IL) bonds, cash/alternatives and property. Panel A refers to the full sample of pension funds, whereas Panel B focuses on private-sector funds (i.e., those sponsored by corporates) and Panel C on public-sector funds (i.e., those sponsored by local authorities).

Table A2: Evolution of Portfolio Weights by Sponsor Type

	Tot. Eq.	UK Eq.	Int. Eq.	Tot. Bo.	UK. Bo.	Int. Bo	UK IL	CA	Prop.
Panel A: Private Funds									
Sample 1995-2012									
$\Delta\log(\omega_{jt})$	-2.85	-5.35	-0.89	6.49	7.53	9.24	5.57	4.79	0.93
$r_{jt}-r_{pt}$	0.20	0.49	-0.38	-0.24	-0.12	-0.22	-0.02	-2.19	0.26
$ncf_{jt}-ncf_{pt}$	-3.05	-5.84	-0.52	6.73	7.65	9.46	5.59	6.98	0.67
corr(r,ncf)	-0.18	-0.23	-0.06	-0.23	-0.16	-0.12	-0.02	-0.12	-0.15
% var(r)	84.09	75.03	89.56	65.56	69.35	16.89	70.67	20.20	84.75
% cov(r,ncf)	8.82	13.44	2.97	16.23	11.36	8.37	1.70	8.83	7.60
% var(ncf)	7.08	11.53	7.48	18.21	19.29	74.75	27.63	70.96	7.65
Sample 2008-2012									
$\Delta\log(\omega_{jt})$	-3.41	-7.53	-1.95	1.94	2.30	3.17	3.11	3.99	1.12
$r_{jt}-r_{pt}$	0.09	0.32	0.21	2.74	2.56	3.97	2.94	-3.77	-5.03
$ncf_{jt}-ncf_{pt}$	-3.50	-7.85	-2.16	-0.81	-0.27	-0.80	0.17	7.76	6.14
corr(r,ncf)	-0.20	-0.30	-0.10	-0.41	-0.41	-0.23	-0.12	-0.43	0.11
% var(r)	85.98	76.24	87.53	66.43	67.69	24.06	81.02	28.39	91.95
% cov(r,ncf)	8.67	15.18	5.14	22.28	21.93	17.05	7.31	29.92	4.06
% var(ncf)	5.35	8.58	7.33	11.30	10.38	58.89	11.66	41.70	3.99
Panel B: Public Funds									
	Tot. Eq.	UK Eq.	Int. Eq.	Tot. Bo.	UK. Bo.	Int. Bo	UK IL	CA	Prop.
Sample 1995-2012									
$\Delta\log(\omega_{jt})$	-0.85	-2.50	1.04	3.98	6.66	-0.56	-3.39	4.65	3.11
$r_{jt}-r_{pt}$	0.69	0.85	0.36	-0.40	0.09	-1.28	0.27	-2.68	-0.60
$ncf_{jt}-ncf_{pt}$	-1.54	-3.35	0.67	4.38	6.57	0.72	-3.66	7.33	3.71
corr(r,ncf)	-0.33	-0.40	-0.07	-0.17	-0.10	-0.19	-0.19	-0.22	0.01
% var(r)	81.43	73.65	89.92	66.67	57.11	42.05	78.28	34.74	94.79
% cov(r,ncf)	13.52	18.76	3.55	12.40	8.44	15.90	11.02	17.89	0.52
% var(ncf)	5.05	7.59	6.53	20.93	34.45	42.05	10.70	47.37	4.69
Sample 2008-2012									
$\Delta\log(\omega_{jt})$	-0.39	-2.85	0.64	2.41	2.06	0.33	-3.93	2.22	-0.69
$r_{jt}-r_{pt}$	1.03	1.08	1.33	2.94	2.70	3.70	2.88	-2.80	-6.34
$ncf_{jt}-ncf_{pt}$	-1.42	-3.93	-0.69	-0.54	-0.64	-3.37	-6.81	5.01	5.65
corr(r,ncf)	-0.42	-0.40	-0.16	-0.36	-0.24	-0.27	-0.25	-0.47	0.11
% var(r)	83.05	74.82	91.61	78.29	82.71	55.57	78.55	59.73	92.83
% cov(r,ncf)	13.77	18.33	5.42	15.60	11.04	20.15	12.87	26.76	3.87
% var(ncf)	3.18	6.85	2.97	6.10	6.25	24.27	8.59	13.51	3.30

The table reports the mean (annualized) percentage change in the average pension fund's portfolio weights, $\Delta\log(\omega_{j,t})$, and its decomposition into the return differential across assets classes, $(r_{j,t}-r_{p,t})$, and shifts in net cash flows across asset classes, $(ncf_{j,t}-ncf_{p,t})$. $\Delta\log(\omega_{j,t})\simeq(r_{j,t}-r_{p,t})+(ncf_{j,t}-ncf_{p,t})$, where $r_{j,t}$ is the value-weighted rate of return on UK pension funds' holdings of asset class j; $ncf_{j,t}$ is the rate of net cash flow into that asset class during month t; $r_{p,t}$ is the value-weighted return of the total portfolio during month t; and $ncf_{p,t}$ is the net cash flow into the total portfolio during month t. Associated with this is the variance decomposition $\text{var}(\Delta\log(\omega_{j,t}))\simeq\text{var}(r_{j,t}-r_{p,t})+\text{var}(ncf_{j,t}-ncf_{p,t})+2\text{cov}(r_{j,t}-r_{p,t},ncf_{j,t}-ncf_{p,t})$. We report the monthly variance of changes in portfolio weights due to the variance of return differentials, var(r), the variance of net cash flow differentials, var(ncf), and the covariance between these, cov(r,ncf) (expressed in percentages). Results for the period from January 1995 to December 2012 are reported in Panel A, while those for the 'crisis period' from January 2008 to December 2012 are reported in Panel B. 'CA' refers to cash/alternatives and 'UK IL' refers to UK index-linked bonds.

Table A3: Momentum Trading

	Cash Flows		**Adj. Weights**	
	avg($\beta_{1,t}$)	avg($\beta_{2,t}$)	avg($\beta_{1,t}$)	avg($\beta_{2,t}$)
(1)	42.96	-4.18	54.50	-5.02
	[19.77]	[-1.73]	[26.28]	[-2.09]
(2)	44.95	-6.91	50.29	-6.97
	[17.92]	[-2.55]	[18.99]	[-2.36]

The table reports the average betas and time-series t-statistics resulting from the following cross-sectional regressions

$$\Delta_{j,t} = \beta_{1,t}\Delta_{j,t-1} + \beta_{2,t} r^{PG}_{j,t-1} + \varepsilon_{j,t},$$

where $\Delta_{j,t}$ is the standardized fraction of pension funds buying asset class j (Panel: Cash Flows), or increasing the return-adjusted weight in j in month t (Panel: Adj. Weights) and $r^{PG}_{j,t-1}$ is the standardized peer-group return of asset j in month t. Specification (1) includes the seven asset classes: UK equities, international equities, UK bonds, international bonds, UK index-linked bonds, cash/alternatives and property. Specification (2) excludes cash/alternatives, focusing on the remaining six asset classes.

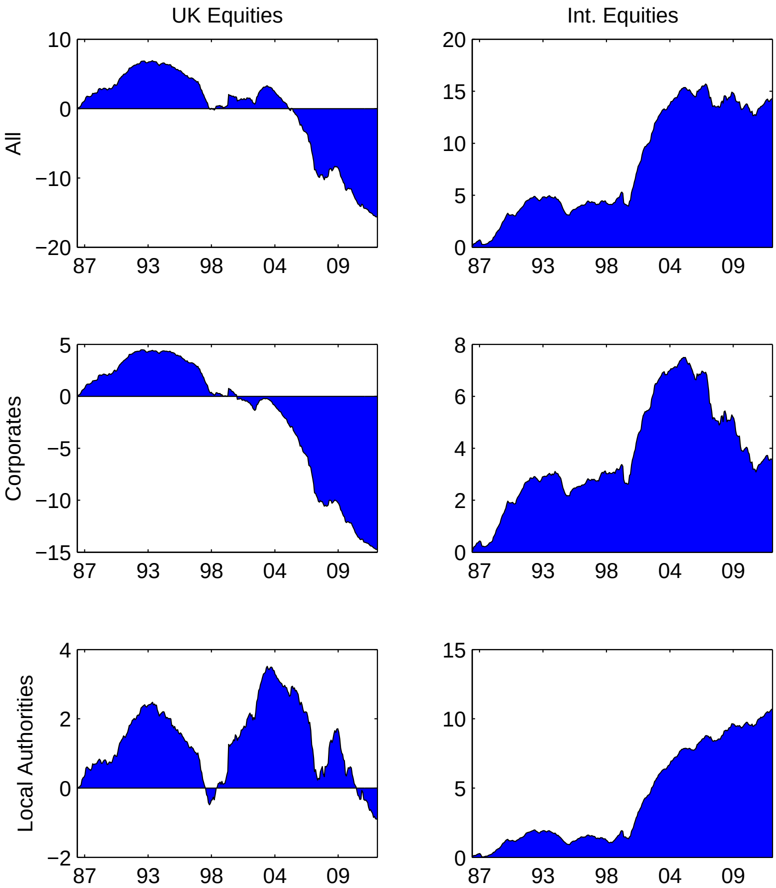


Figure A1: Cumulative Equity Flows (in Billion Pounds)

Note: The figure shows UK private- and public-sector cumulative flows (net investment) in total, UK and international equities for the period from January 1987 to December 2012.

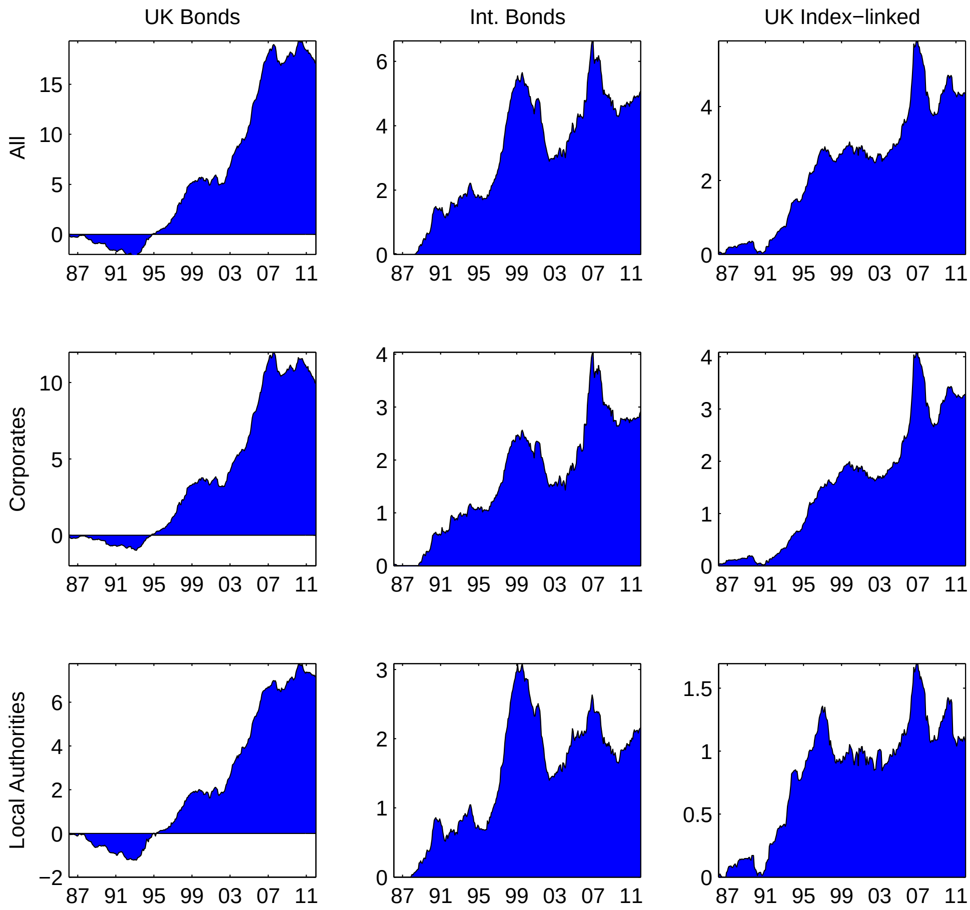


Figure A2: Cumulative Bond Flows (in Billion Pounds)

Note: The figure shows UK private- and public-sector cumulative flows (net investment) in UK and international conventional bonds and in UK index-linked bonds for the period from January 1987 to December 2012.

A.II Herding Test on Simulated Portfolio Flows and Weights

Here, we simulate the fund portfolio for a fixed number of funds (nF) and for different numbers of asset classes (nA), or securities, under the no herding assumption. For a given fund i, and a fixed number of assets nA, we simulate the fund i's portfolio. To do that, for each asset class j, we simulate the fund net investment $(CF(1:T,i,j))$ and returns $(r(1:T,i,j))$, where *1:T* is the time period. Having fixed the initial holdings at $t=0$ for the asset class j, we then recover the *z*-iteration holdings (stock) by using the following dynamics, $H^z(t+1,i,j) = H^z(t,i,j) \times (1+r(t+1,i,j)) + CF(t+1,i,j)$, as in Blake, Lehmann and Timmerman (1999). The weights associated with the *z*-iteration are then easily computed. We repeat the same procedure for each fund in turn. Then, for the *z*-iteration portfolio, we compute the Sias' (2004) herding measure:

$$\varDelta^z_{j,t} = \beta^z_t \varDelta^z_{j,t-1} + \varepsilon^z_{j,t}. \tag{A.II.1}$$

and the associated test statistics. We repeat the same steps for Z iterations. We therefore recover the empirical distributions for the $\beta^z = \sum_{t=1}^{T} \beta^z_t$ and its test statistics. We perform the analysis separately for flows and weights. Specifically, we set the parameters as follows:

- number of iterations, Z = 50,000.
- number of funds, nF = 189, same number of funds as in our data set.
- number of months T = 240, roughly the size of our data set.
- number of asset classes, nA = [5 7 8 10 20 25 30 40 50].

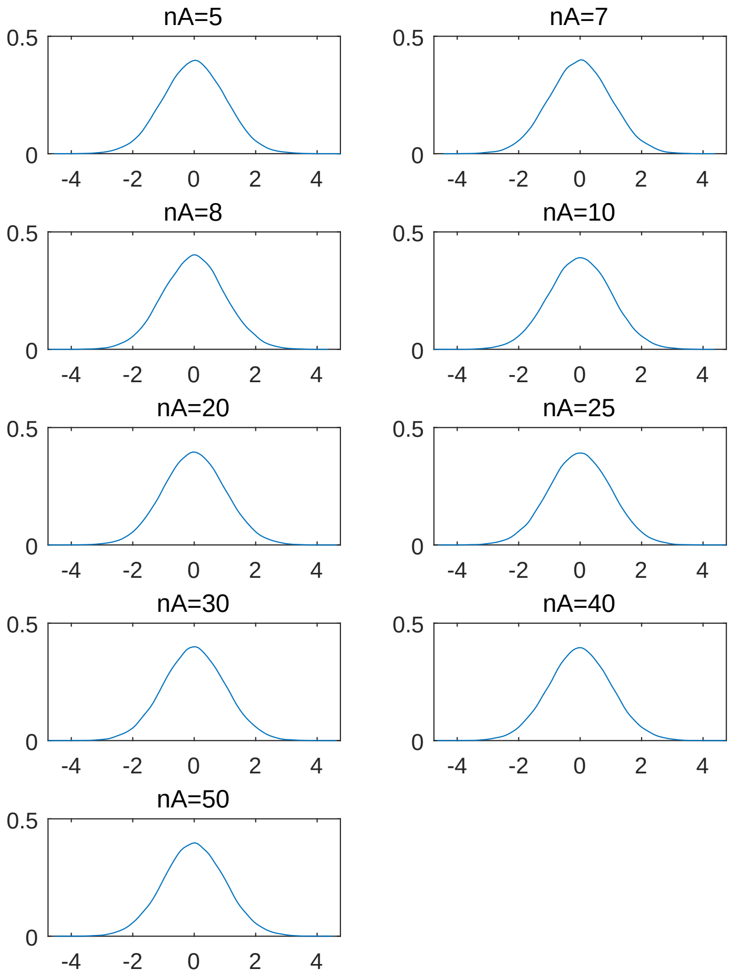
The empirical confidence intervals are reported at 5% confidence level. The asymtotic *p*-value is computed as the fraction of times/iterations the test statistics is outside the 5% critical values of the normal distribution [-1.96; 1.96]. We present the 5% empirical critical values and their asymptotic p-values in Table A4, and the empirical densities for flows and weights are shown in Figures A3 and A4, respectively. The simulations are robust to changing the number of funds and the parameters used to simulate the net investments and returns.

Table A4: Herding Test Statistics: Empirical Critical Values and Asymptotic p-values

	Panel A: Flows			Panel B: Weights		
	lb (2.5 %)	ub (97.5 %)	p-value	lb (2.5 %)	ub (97.5 %)	p-value
nA = 5	-1.98	1.97	0.05	-1.97	1.96	0.05
nA = 7	-1.97	1.98	0.05	-2.02	1.97	0.05
nA = 8	-1.96	1.97	0.05	-1.98	1.97	0.05
nA = 10	-1.98	1.98	0.05	-1.97	1.98	0.05
nA = 20	-1.97	1.99	0.05	-1.99	1.95	0.05
nA = 25	-1.98	1.96	0.05	-1.99	1.96	0.05
nA = 30	-1.97	1.98	0.05	-2.00	1.98	0.05
nA = 40	-1.98	2.02	0.05	-1.96	1.97	0.05
nA = 50	-1.98	1.99	0.05	-1.98	1.99	0.05

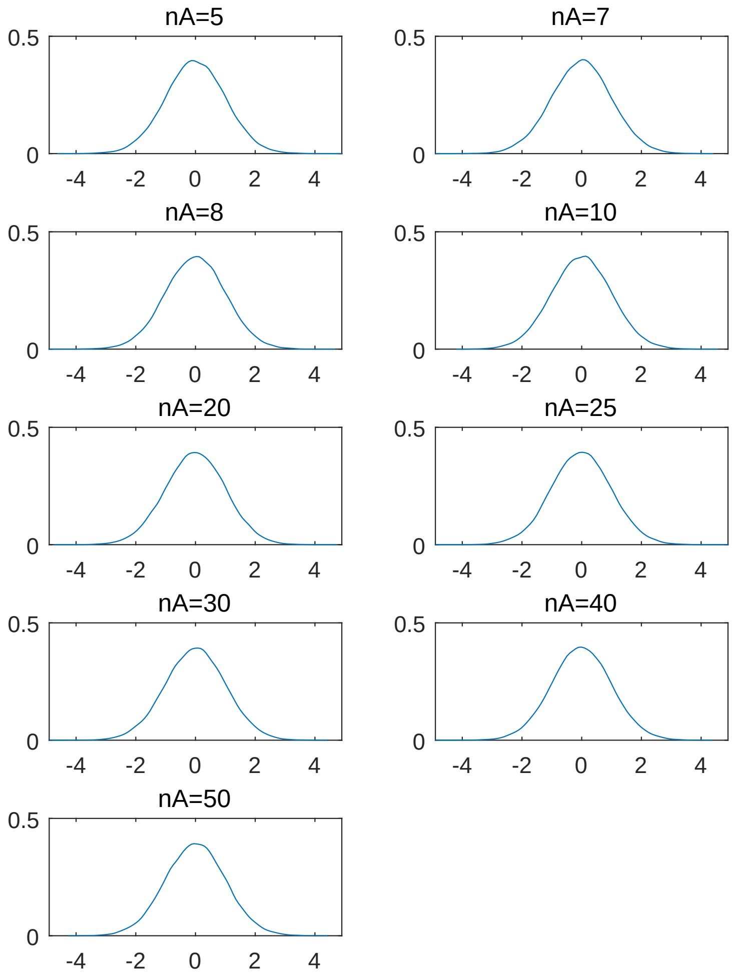
This table presents the empirical critical values and the asymptotic p-values at the 5% level for the Sias' herding test for the following number of asset classes, nA=[5 7 8 10 20 25 30 40 50], for a sample of 189 funds over a period of 20 years, performing 50,000 simulations. We perform the analysis on portfolio flows in Panel A, and on portfolio weights in Panel B.

Figure A3: Empirical Distribution of the Herding Test Statistics on Flows



Note: The figure shows the empirical density of the Sias' herding test statistics for the following number of asset classes, nA=[5 7 8 10 20 25 30 40 50], for a sample of 189 funds over a period of 20 years, performing 50,000 simulations. The test is implemented on the portfolio *flows* under the null hypothesis of no herding.

Figure A4: Empirical Distribution of the Herding Test Statistics on Portfolio Weights



Note: The figure shows the empirical density of the Sias' herding test statistics for the following number of asset classes, nA=[5 7 8 10 20 25 30 40 50], for a sample of 189 funds over a period of 20 years, performing 50,000 simulations. The test is implemented on the portfolio *weights* under the null hypothesis of no herding.

A.III An Additional Herding Measure

Table A5: LSV Herding Measure

Panel A: Flows	UK Eq.	Int. Eq.	UK Bo.	Int. Bo.	UK IL	Cash	Prop	Tot.	Tot. Ex CA
mean	0.089	0.088	0.100	0.115	0.114	0.071	0.117	0.099	0.104
t-stat	(24.77)	(23.38)	(23.12)	(23.11)	(20.26)	(22.50)	(26.50)	(54.28)	(51.79)
median	0.078	0.074	0.086	0.103	0.087	0.059	0.109	0.092	0.097
Panel B: Return-Adjusted Weights	UK Eq.	Int. Eq.	UK Bo.	Int. Bo.	UK IL	Cash	Prop	Tot.	Tot. Ex CA
mean	0.084	0.094	0.079	0.084	0.088	0.106	0.093	0.090	0.087
t-stat	(22.26)	(23.16)	(24.96)	(23.15)	(26.51)	(23.13)	(31.19)	(52.55)	(48.07)
median	0.070	0.076	0.069	0.074	0.078	0.089	0.088	0.085	0.081

The table reports the LSV herding measure (mean), presented for each of the seven asset classes and for the total portfolio, with (Tot.) and without (Tot. Ex.) the cash/alternatives class. In Panel A, The LSV measure for month t and asset class j is defined as:

$$H(j,t) = |Raw\Delta_{j,t} - \overline{Raw\Delta_t}| - AF(j,t), \tag{A.III.1}$$

where $Raw\Delta_{j,t}$ is the raw fraction of pension funds buying asset class j in month t, $\overline{Raw\Delta_t}$ is the expected proportion of funds buying in that month relative to the number of active funds, and $AF(j,t)$ is an adjustment factor for asset class j in month t, which accounts for different number of active funds. Specifically, $AF(j,t)$ is computed by assuming that the number of funds buying asset class j in month t follows a binomial distribution with probability $\overline{Raw\Delta_t}$ (see LSV, 1992, for details). The LSV herding measures are computed for each asset class and month, and then averaged across classes in column Total and Total ex CA. t-statistics are reported in parentheses below the LSV herding measure (mean). We also report the median of the LSV herding measure (median). In Panel B, we repeat the analysis using return-adjusted weights rather than cash flows; we identify pension fund n as a buyer (seller) of asset class j, if the return-adjusted portfolio weight of asset class j increased (decreased), i.e., the flow differential is positive (negative). The data cover the period January 1987 -December 2012.