The Market for Lemmings: Is the Investment Behavior of Pension Funds Stabilizing or Destabilizing?[*]

David Blake[†]   Lucio Sarno[‡]   Gabriele Zinna[§]

Abstract

Pension funds are large institutional investors, and yet very little is known about their investment behavior. Using a unique dataset that covers UK defined-benefit pension funds' asset allocations over the past 25 years, we show that pension funds display strong herding behavior when moving in and out of different asset classes and they herd in subgroups (defined by size and sector type), consistent with the notion of 'reputational' herding. We also find that pension funds mechanically rebalance their portfolios in the short term in response to valuation changes, and they systemically switch from equities to bonds as their liabilities mature. Furthermore, the median fund is an index matcher, hence failing to earn a long-run liquidity premium. Overall, we uncover evidence that pension funds do not play the stabilizing role one would expect from long-term investors.

Keywords: Institutional investors; herding; portfolio rebalancing; liquidity premium.

JEL Classification: F34; G12; G15.

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. And that, naturally, exacerbates price movements'. (Wall Street Journal, October 17, 1989)

'Myriad new unseasoned hedge and commodity funds are started precisely to exploit the distorted incentives of the pension or insurance fund managers who queue like lemmings to dutifully place the public's money. (Rajan, October 6, 2006)

As long-term investors, one would expect pension funds to focus on their long-term investment strategy. Pension funds also have predictable cash outflows and hence are unlikely to face substantial unanticipated short-term liquidity needs. They are therefore in a position to provide liquidity to financial markets at times when it is needed, for example, by investing in illiquid assets during periods of market turmoil or financial crises, thereby helping stabilize financial markets and earning a liquidity premium in return. However, pension fund managers tend to have similar benchmarks. This, in turn, might create a fear of relative underperformance compared with the peer group of fund managers and hence an incentive for pension funds to herd, i.e., to buy and sell the same asset at the same time; this type of herding is often termed 'reputational' herding (Scharfstein and Stein, 1990).

In addition, 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). 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 and also, because of the size of the funds involved, institutional herding is more likely to produce a bigger price impact than individual herding (Nofsingerand and Sias, 1999). If pension fund herding results in procyclical or positive-feedback investment strategies – buying assets in a rising market, selling in a falling market – this could have a destabilizing effect on financial markets (Wermers, 1999). In essence, there are good reasons why the investment decisions of pension funds may be stabilizing or destabilizing for financial markets, and this issue is 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; Bank of England, 2014).

LSV (1992) is one of the few studies to examine these issues in the context of the pension fund industry: they find no evidence of pension fund herding, which suggests that pension funds do not engage in destabilizing practices. However, their conclusion 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 herding might be more prevalent among subgroups of pension funds rather than in aggregate, but their data does not allow them to test this interesting conjecture.

We investigate both these issues in this paper. First, we focus on herding in asset classes rather than in individual stocks. Second, we investigate whether herding is more predominant in subgroups, consistent with reputational herding. We classify pension funds into subgroups according to their size and sponsor type. Our analysis is based on 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.

Our empirical analysis establishes some clear facts about the investment behavior of pension funds. *First*, we find robust evidence of reputational herding in the investments of pension funds. Specifically, by implementing the herding test developed by Sias (2004) and Choi and Sias (2009), we find 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. There are a number of possible reasons for herding. In addition to reputational concerns, herding could be due to habit investing or momentum (i.e., positive feedback) trading. Our evidence comes down in favor of reputational herding, and we show that pension funds herd in subgroups, supporting LSV's conjecture. Specifically, we double sort funds by sponsor

type (private-sector and public-sector) and by size (small, medium and large), and we find that: (i) public-sector funds follow other public-sector funds of similar size; similarly, (ii) large private-sector funds strongly follow other large private-sector funds.[1]

Second, our findings also indicate strong short-term 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. Further, although we do not have any 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. This analysis suggests that the average pension fund – as represented by the peer-group benchmark – appears to rebalance its long-run portfolio in a way that is liability matching. As the maturity of pension fund liabilities has increased, large private-sector pension funds (in particular) have systematically switched from UK equities to conventional and index-linked bonds.[2]

Given the above results, we address the natural question whether pension fund investment behavior is stabilizing or destabilizing for asset prices. Institutional herding is often considered to be evidence of procyclical investment behavior with destabilizing effects on financial markets (Papaioannou, Park, Pihlman and van der Hoorn, 2013). LSV's view, however, is that herding alone is not sufficient to conclude that pension fund investment behavior is destabilizing. If pension funds herd, they are more likely to move prices, but their behavior is destabilizing only to the extent that they move market prices away from, rather than towards, their equilibrium values. So, for example, if pension funds were momentum traders, but better informed than other investors, then their trading might still be stabilizing. This argument also implies, however, that showing that pension funds are contrarian investors is not sufficient to conclude that pension fund investment behavior is stabilizing. A key issue, therefore, is whether the trading of the average pension fund reflects superior information. The answer to this question is no. We find that pension funds *mechanically* rebalance their portfolios in the short term

---

[1]It is important to note that there have been regulatory and accounting interventions during the period analyzed that provided externally induced reasons for funds to herd and which could have increased the procyclicality of their investment strategies. We discuss these issues in the next section.

[2]However, public-sector funds and smaller private-sector funds display interesting differences in asset allocations, which we document and discuss later.

if relative valuation changes in the different asset classes lead to violations in their mandate restrictions. In the long term, there are systematic changes in the strategic asset allocation 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). As a result, the average pension fund's investment behavior can still be destabilizing, since it does not respond to the release of new information, with the risk that market prices can be moved away from their fundamental values.[3]

We also 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 fund managers herd around the average fund manager who generates the peer-group average return and who is, in turn, no more than a 'closet index matcher'.

Third, we find that pension funds have failed to capture a positive liquidity premium over our sample period, in contrast with the expectation that long-horizon investors should be able to provide liquidity to financial markets and earn adequate compensation for this important role. Our analysis starts from the premise that, although we find evidence of pension fund herding, there might still be cross-sectional differences in their ability to earn a liquidity premium by deviating from the peer-group allocation (which reflects the component of returns resulting from their active management investment).[4] Thus, we study portfolios resulting from grouping the funds according to their time-varying exposure to liquidity, following, e.g., Hu, Pan and Wang (2013). We find no evidence of liquidity premia being priced in the cross

---

[3]This risk is, in fact, confirmed by a recent study on institutional investors by Reca, Sias and Turtle (2014), showing that non-hedge fund demand shocks, in contrast with hedge-fund demand shocks, systematically drive prices away from fundamental values. Note that this study focuses on crowds' behavior in individual long-only equity trades. Moreover, this result is consistent with other evidence which shows the poor market timing ability of pension funds (e.g. Blake and Timmermann, 1999).

[4]Individual funds, for example, differ in the maturity structure of their liabilities and in the strength of their sponsor covenant. Another important factor is fund size. On the one hand, smaller funds might be able to earn a larger liquidity premium, since they are able to react more quickly to liquidity shocks than larger funds where 'size is the anchor to performance' (Chen, Hong, Huang, Kubik, 2004). On the other hand, larger funds might have the scale not enjoyed by smaller funds to invest in illiquid assets such as property and infrastructure. So some funds might be in a better place than other funds to invest in illiquid assets.

section of pension funds' portfolio returns in excess of the peer-group return. Funds that are more exposed to liquidity risk do not generate systematically higher returns than less exposed funds. Instead we find that, looking at their total portfolios over the full sample period, the less exposed funds earn a premium (although it is not statistically significant) over the more exposed funds.[5]

This cross-sectional analysis is based on active returns, i.e. fund returns in excess of the benchmark returns. This result suggests that pension funds do not significantly differ in their ability to extract liquidity premia. However, this evidence is not yet sufficient to conclude that pension funds do not exploit the liquidity shortages of other investors: if each fund were to invest in illiquid assets, this would be reflected in the peer-group returns and therefore it would not be captured by the active returns. For this reason, we repeat the portfolio sort analysis on funds' returns in excess of the risk-free rate. We find that average excess returns, regardless of the portfolios considered, are not different from zero. This allows us to conclude that not only are funds more exposed to liquidity risk unable to generate a positive return in excess of the peer-group return (as also shown by the active return analysis), but also that pension funds are unable to exploit the liquidity shortages of other investors. Both results are consistent with the earlier finding that pension funds tend to herd around the average fund which is, in turn, an index matcher, as the indices only include the most liquid securities. Taken together, the results of the portfolio sort analysis provide compelling evidence indicating that pension fund investment behavior is unlikely to have stabilizing effects on financial markets.

The rest of the paper is organized as follows. Section 2 discusses the relevant institutional features of the pension fund industry in the UK, and Section 3 describes our data in detail. Section 4 provides empirical results on pension funds' herding. Section 5 examines which factors drive pension fund returns and net investment. Section 6 provides cross-sectional tests of the pension funds' ability to extract liquidity premia. Finally, Section 7 concludes the paper. Further details are provided in the Appendix, and a number of extensions and robustness checks are reported in the Internet Appendix.

---

[5]We also find that the portfolio returns of smaller funds are more exposed to liquidity shocks than larger funds. However, when we look at the separate asset classes, we only find evidence of a liquidity premium being priced in the cross-section of pension fund returns resulting from their investments in international equities and this holds independent of fund size.

5

2   The UK Pension Fund Industry: Institutional Details

For most of its history, the UK pensions industry has been subject to a light regulatory framework with little need for accounting transparency. However, a number of regulatory and accounting reforms were introduced over the past two decades aimed at enhancing the resilience and transparency of the UK pension fund industry. As a result, these reforms, when combined with the increasing maturity of pension funds' liabilities over the same period, led to substantial changes in the asset allocation of pension funds, making their demand for assets more inelastic and potentially increasing the procyclicality of their investment strategies (Papaioannou, Park, Pihlman and van der Hoorn, 2013; Haldane, 2014).

The Pensions Act of 1995 introduced the Minimum Funding Requirement (MFR) to increase the likelihood that pension plan members would be paid in full even if the sponsoring company became insolvent (Blake, 2003).[6] While the MFR did not prescribe pension funds to invest in particular asset categories, some key discount rates used in calculating MFR liabilities were based on gilt (UK government bond) yields, so pension fund managers were drawn towards gilts as the natural matching asset for MFR liabilities, on the grounds that there is a reduced risk of failing the test if the asset portfolio reflects the discount rates required to value liabilities (Blake, 2003, p. 109). The MFR also encouraged pension fund managers to lower their weighting in equities and other volatile assets, as the relatively higher volatility of these asset categories hinders the ability of funds to meet the MFR every three years. The MFR had a significant effect in distorting the long end of the gilts market by driving down yields as funds switched into long-term bonds at the same time. As a result of these distortions, the Pensions Act 2004 abolished the MFR, replacing it with a new scheme-specific funding standard from December 2005 which the government hoped would be less distortionary. Companies were given 10 years to eliminate plan deficits. However, these changes did little to change the distortion to long-term interest rates (see Haldane, 2014).[7]

---

[6]Pension funds which failed to meet the MFR on their valuation date were given one year to reach 90% funding and five years to reach full funding.

[7]Greenwood and Vayanos (2010) investigate the downward pressure exerted by UK pension funds' increased demand for long-dated gilts on long-term yields around the time of the Pensions Act 2004. More generally, Chan and Lakonishok (1995) show that the short-term demand curve for stocks of institutional investors is not perfectly elastic, and that a large excess demand for a stock can only be accommodated at a higher price

From 1 January 2005, Financial Reporting Standard 17 became mandatory. Under this accounting standard, a listed company is required to measure both DB pension plan assets and liabilities at either market value or fair value (using an AA corporate bond discount rate) and to recognize the plan's surplus/deficit on the company's balance sheet. Moreover, in April 2005, following the Pensions Act 2004, the Pension Protection Fund (PPF) was introduced, providing compensation for DB plan members if their employer becomes insolvent and the pension plan is underfunded. All companies with DB plans pay a risk-based levy to the PPF which depends on the degree of underfunding, the strength of the sponsor covenant as measured by the sponsor's credit rating, and the riskiness of the fund's investment strategy.

All these changes had a strong influence on pension funds' asset-liability management strategies, linking strategic asset allocation much more closely to the development of plan liabilities. Pension funds became more likely to follow liability-driven investment (LDI) strategies, reducing their historically high weight in equities and replacing these with fixed-income and inflation-linked government bonds, together with interest rate and inflation swaps.[8]

There are other institutional features of the UK pension fund industry which are relevant to explaining a pension fund's investment behavior. In particular, a pension fund's asset allocation is determined by the interaction between the sponsoring company, plan trustees (i.e., fiduciaries), investment or actuarial consultants, and asset managers. The UK legal framework under which pension plans operate is trust law. This gives a key role to trustees who have a legal obligation to run the plan in the best interests of the beneficiaries. The trustees must determine the plan's strategic asset allocation and agree a funding strategy with the sponsor. However, most trustees are part time and unskilled in investment matters and rely heavily on the advice of their consultants and asset managers. The UK consultancy and asset management industries are much more heavily concentrated than in other parts of the world.[9] This is likely to lead to trustees in different plans being given similar advice at the same time. Again this could, in turn, encourage procyclical herding behavior.

---

and lower yield.

[8]Most pension benefits in the UK are index-linked to inflation.

[9]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).

In theory, the asset management mandate might encourage procyclicality or countercyclicality. For example, a mandate with a peer-group benchmark is likely to lead to procyclicality, while a mandate with an external market index as a benchmark with a tracking error limit might induce countercyclical behavior. As another example, mandates may contain restrictions on the credit ratings of bond holdings that might lead to mechanical procyclical responses to rating changes. Some asset managers, however, use laddering strategies that might act to mitigate procyclicality by introducing thresholds at which assets are bought and sold against broader market moves, and the prevalence of such strategies could be significant enough to act as a countercyclical force.[10]

In summary, prior to the mid-1990s, UK pension funds were able to optimize the risk-return profile of their assets, since their liabilities were 'immature'. After the mid-1990s, a combination of regulatory and accounting changes, coupled with the increasing maturity of pension funds and the increasing volatility of equity markets post-2000, have shifted attention to LDI strategies. To the extent that any sell-off of equities, as part of a de-risking strategy, takes place at a time of falling equity prices, pension fund asset demands can become procyclical, exerting additional downward price pressure. Moreover, the reliance on a small number of consultants and asset managers and the widespread use of peer-group benchmarks are likely to induce pension funds to herd in the short term. Also, unexpected valuation changes, resulting, for example, either from changes in market prices or liquidity conditions, may cause pension funds' asset weights to deviate from their optimal long-run allocation. In response, pension funds might rebalance their portfolios, by cutting back on relatively strongly performing asset classes and buying into relatively under-performing asset classes. Since this behavior is not driven by changing expectations about returns and risks, this automatic rebalancing can be an obstacle to asset prices reaching their fundamental values, and, hence, can be destabilizing.

---

[10]A pension plan's asset allocation will also be influenced by its funding status and the strength of the sponsor covenant. A fully funded plan with a strong sponsor covenant has greater flexibility in choosing its investment strategy and is better placed to behave in a contrarian fashion. It could also invest in illiquid assets and earn a liquidity premium. However, the maturity of the fund is also an important determinant of its investment strategy. As funds mature, they would be expected to move away from equities and into bonds, whatever the 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).

3 Data and Descriptive Statistics

The data used in this paper were provided to us by State Street Investment Analytics (SSIA hereafter)[11] and consist of monthly observations on 189 UK DB pension funds from January 1987 to December 2012. The data are in the form of an unbalanced panel, covering a total of 108 corporate and 81 local authority pension funds.[12] For each fund, we have data on the overall portfolio (i.e., total assets) and the following seven constituents: equities (UK and international), fixed-interest bonds (UK and international), index-linked bonds (UK only), cash/alternatives, and property.[13] 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 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

---

[11]The SSIA is one of the two key performance measurement services in the UK, the other is CAPS (Combined Actuarial Performance Services).

[12]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.

[13]Cash/alternatives is a catch-all residual category that includes, e.g., both Treasury bills and hedge funds. However, the investment in hedge funds is largely concentrated in the second part of the sample.

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: local authorities still operate open DB pension plans, while most of the corporate DB plans are now closed to new members. The 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 sponsor covenant is also generally stronger in local authority funds than in corporate funds arising from the taxation powers of local authorities, and this enables local authority funds to take more risk.[14]

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 different 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 2008-2012 period, although this has

---

[14]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).

mainly been by local authorities.

The government ended the tax relief on UK dividend payments for pension funds 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 4 shows very different net investment behavior by the two different sectors. 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 types of funds show similar behavior when it comes to bonds, however, as Figure 5 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.

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.[15]

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

---

[15]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.

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, our 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.[16]

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, 2002). The set of external 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); and Investment Property Databank (IPD) Annual Property Index (property). All these indices are denominated in UK pounds, and assume that investment income is reinvested (gross of tax) and returns are calculated on a time-weighted basis and are available on Datastream.

The adoption of peer-group benchmarks and the practice of evaluating pension funds against each other may induce herding in their investment strategies (LSV, 1992). Moreover, despite pension funds having long-term objectives, their performance is generally assessed over the short term, typically quarterly. The high frequency of assessment against a peer-group benchmark may limit the extent to which they engage in active management or exploit their comparative advantage in earning a liquidity premium.

---

[16]The absence of survivor bias can be seen by comparing the summary statistics on the peer-group 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. The other half is 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 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.

4   Herding

Institutions are more likely to herd than individual investors for a number of reasons. First, institutions know more about each others' trades than do individual investors (Banerjee, 1992; Bikhchandani, Hirshleifer and Welch, 1992). Second, institutional investors may react to the same exogenous signals, leading to the so-called 'investigative' herding (Froot, Scharfstein and Stein, 1992), and signals that reach institutions are generally more highly correlated than signals that reach individuals (LSV, 1992). Third, asset managers are evaluated against each other and this, in turn, generates a fear of relative underperformance that induces 'reputational' herding. In essence, asset managers are incentivized to hold the same asset mix as other asset managers and sometimes even the same securities (Scharfstein and Stein, 1990).

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 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. Furthermore, even without herding, funds with a similar maturity structure of liabilities would be expected to have a similar asset mix, although not necessarily the same securities within an asset class.

4.1   Evidence on Herding

We test whether pension funds herd into and out of an asset class by adapting the test proposed first by Sias (2004) for herding in individual stocks, and then used by Choi and Sias (2009) for herding in industry groups. The test 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.[17] However, it is clear that such positive correlation is only a necessary

---

[17]LSV (1992) based their analysis on a different test of herding. See Sias (2004) and Choi and Sias (2008) for a detailed discussion of the different methodologies.

condition for herding, as it is also consistent with pension funds following their own previous month trades, so that pension funds may simply be following their own mandate rather than herding. 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 correlation is roughly 44 percent in Specification (1), and this increases to 47 percent in Specification (2); when we exclude cash/alternatives, the correlation is estimated with more precision, with the average t-statistic being significant at the 10 percent level.

However, these results should be taken with caution, both because the statistical signif-

icance of β_t is weak and, more importantly, because a positive β_t is not complete proof of pension fund herding, as it may simply reflect short-term portfolio rebalancing or even systematic but gradual net purchases of an asset class over time (i.e., pension funds 'following their mandate' rather than 'following others'). Put another way, β_t aggregates very different information which can be decomposed into two parts: (1) individual pension funds rebalancing their portfolio over adjacent months (*following their mandate, m*), and (2) pension funds following other pension funds into and out of the same asset classes (*herding, h*). Sias (2004) shows that the correlation captured by β_t can be partitioned accordingly into these two components, denoted β_t^m and β_t^h, so that $\beta_t = \beta_t^m + \beta_t^h$. Analysis of the two components β_t^m 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:

$$
\begin{aligned}
\beta_t \;=\;& \rho\left(\Delta_{j,t}, \Delta_{j,t-1}\right) = \beta_t^m + \beta_t^h = \\[2mm]
=\;& \left[\frac{1}{(J)\,\sigma\left(Raw\,\Delta_{j,t}\right)\sigma\left(Raw\,\Delta_{j,t-1}\right)}\right] \\[2mm]
& \times \sum_{j=1}^{J}\left[\sum_{n=1}^{N_{j,t}}\left(\frac{D_{n,j,t}-\overline{Raw\,\Delta_t}}{N_{j,t}}\cdot\frac{D_{n,j,t-1}-\overline{Raw\,\Delta_{t-1}}}{N_{j,t-1}}\right)\right] + \\[2mm]
& \left[\frac{1}{(J)\,\sigma\left(Raw\,\Delta_{j,t}\right)\sigma\left(Raw\,\Delta_{j,t-1}\right)}\right] \\[2mm]
& \times \sum_{j=1}^{J}\left[\sum_{n=1}^{N_{j,t}}\sum_{m=1,m\neq n}^{N_{j,t-1}}\left(\frac{D_{n,j,t}-\overline{Raw\,\Delta_t}}{N_{j,t}}\cdot\frac{D_{m,j,t-1}-\overline{Raw\,\Delta_{t-1}}}{N_{j,t-1}}\right)\right]
\end{aligned}
\tag{4}
$$

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. The first term (β_t^m) denotes the *mandate 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 this term will be zero.

Panel A of Table 2 presents the two components and the time series t-statistics. Both β_t^m 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^m (more than 10 times larger). Thus, while there is evidence of pension funds following their mandate, the pure herding effect strongly dominates.

4.2 Assessing Different Explanations for Pension Fund Herding

Institutional investors may herd for a number of reasons. We focus on the three main motives identified in the literature: correlation between investor cash flows (so-called habit investing), momentum trading and reputational herding. We then relate these motives to pension funds.

4.2.1 Correlated Investor Cash Flows

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 affected by the presence of cross-sectional and time-series correlations in the cash inflows into pension funds (Sias, 2004; and Choi and Sias, 2009). 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 has 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 the 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

16

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):

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

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; $ncf_{n,j,t}$ 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:

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

We now repeat the same steps as before: we first standardize $RawW\Delta_{j,t}$, and then estimate eq. (3) by regressing the standardized fraction of pension funds increasing their weight in asset j at time t (say $\widetilde{\Delta}_{j,t}$) on the standardized fraction of pension funds increasing their weight in asset j at time $t-1$ (say $\widetilde{\Delta}_{j,t-1}$). If the estimated average correlation were partly driven by correlated flows (habit investing), we would expect a lower 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 their mandate'

component increases from 38 percent to 50 percent. This result makes sense given that peer-group benchmarks provide information on weights rather than flows. The implication is that we can rule out habit investing as a source of herding for pension funds.

Thus far, we have analyzed the average correlation of the 'following others' component. We complete the analysis by showing the evolution of herding over time. Figure 6 indicates that the herding correlation is high towards the start of the sample, but it displays a dramatic drop around 1994. The herding correlation exhibits cyclical behavior, reaching values as high as 70 percent around 2003, and then following a downward trend that reaches a minimum of 20 percent at the end of the sample. The figure also shows periods of economic recession as identified by the National Bureau of Economic Research (NBER). It appears that herding increases prior to a recession and decreases immediately after. Figure 6 also seems to indicate that herding decreased in advance of the two main regulatory changes in 1995 and 2004. This makes sense as, in preparing for these changes, pension funds would be more concerned with ensuring that they were compliant with the two Pensions Acts, especially in terms of asset-liability matching, than with watching and responding to how other pension funds were investing.

4.2.2 Reputational Herding

Reputational herding can manifest itself in a number of ways. 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, in turn, might be due to the fact that the funds in the two sectors are evaluated against a sector peer-group benchmark. More generally, Sias (2004) conjectures that if reputational herding is the principal driver of herding, then institutional investors should be more likely to follow similar investor types than different types. We follow Sias (2004) by decomposing 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 (public) funds' average contribution from following other

private (public) funds and the average contribution from following public (private) 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:

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

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 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).[18] 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:

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

where $LA_{j,t-1}$ is the number of public-sector funds trading asset class j in month $t-1$. If private-sector funds' reputational 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, for private-sector funds, there is evidence of reputational herding, i.e. the difference between 'following others of the *same* type' (0.52%) and the 'following others of a *different* type' (0.42%) is positive and statistically significant over consecutive months. In contrast, public-sector funds seem to largely follow private-sector funds. This result seems in contrast with the reputational herding story, but it will become clearer that this is not the case once we investigate the role of size in pension funds' herding.

---

[18]Note that in light of the results of 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 institutions increasing the return-adjusted weight in month t.

Indeed, pension funds may herd more with funds of similar size, since managers are generally evaluated against other managers of funds of similar size.[19] 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 new 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 largely with private-sector funds, which at first glance seems inconsistent with the fact that the asset allocations in the two sectors diverge significantly in the long term, as Figures 2 and 4 show. However, we also found strong evidence in favor of a size effect. For this reason, we test whether the results for herding by sector type change when conditioning on 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 sector 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 by sector type in Panel A by comparing funds of different sector type but of similar size. We find that controlling for size is particularly important. Panel C of Table 3 shows that, once we condition on size, the results for public-sector funds change substantially: public-sector funds now mostly follow other public-sector funds of the same size. That said, it is also evident from Panel C that conditioning on size affects the result for small private-sector funds, suggesting that the size effect prevails over the sector type effect.[20] In contrast, large

---

[19]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, hereafter BRTTW, 2013).

[20]This result is sensitive to what is included in the *other different* category, as Table A2 in the Internet

private-sector funds, and to a lesser extent medium private-sector funds, tend to follow mostly other funds of similar type.

These results, taken together, provide strong evidence that pension funds herd in subgroups, defined by size and sector type, supporting the notion of reputational herding.

4.2.3 Momentum Trading

A large body of literature has investigated momentum trading and found evidence that (some groups of) institutional investors are momentum traders.[21] This literature has mostly focused on mutual fund momentum trading at a 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. There is some evidence of momentum trading in small-cap stocks, but these represent only a tiny fraction of pension funds' total assets. We now investigate pension funds' momentum trading at the level of asset classes.

Momentum trading is 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. Following Sias (2004) and Choi and Sias (2009), we investigate this possibility by adding lagged returns to eq. (3). Specifically, testing for momentum trading requires estimating:

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

where $r^{PG}_{j,t-1}$ is the standardized 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

---

Appendix shows. There we essentially repeat the analysis by populating the *other different* category not only with funds of similar size and different sector type, but also by including all other funds of different size irrespective of sector type. In this case, the coefficient associated with average different type decreases from 1.03 percent to 0.69 percent when medium and large funds, both public or private, are included into the category of *other different*. This means that now small private-sector funds also tend to follow other small private-sector funds more than other funds of different size or type. Table A2 in the Internet Appendix also shows that the results change very little for the remaining subgroups.

[21]See Grinblatt and Titman (1989, 1993), Grinblatt, Titman and Wermers (1995), Nofsinger and Sias (1999), Wermers (1999, 2000), Sias, Starks and Titman (2002), Sias (2004) and Choi and Sias (2008).

imply that herding is driven by momentum trading. However, we find no evidence of momentum trading by pension funds, as reflected in a statistically insignificant $\beta_{2,t}$.[22] Moreover, the coefficient on lagged demand, $\beta_{1,t}$, is broadly unchanged, i.e., the inclusion of lagged returns does not alter the estimated impact of lagged demand.

5 Understanding Pension Fund Returns and Net Investment

Thus far, we have established that pension funds engage in reputational herding, but do not engage in habit investing or momentum trading to any great extent. Further, they largely herd in sector and size subgroups at the level of asset classes. If pension funds 'follow others' (or herd) when they trade in asset classes, it is possible that they have a destabilizing effect on financial markets. However, their trading would be destabilizing only to the extent that they move prices away from, rather than towards, equilibrium values (e.g., LSV, 1992). In other words, if pension funds were better informed than other investors, their trading activities might well be stabilizing. Therefore, in this section we further investigate what drives returns and net investment of pension funds as a way to better understand what pension funds do in their asset allocation strategy, and whether their trading actions reflect superior information.

5.1 Factors Driving Pension Fund Returns

To determine what drives pension fund returns, 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. The external indices were discussed in Section 3.2, so here we focus on our preferred measure of liquidity. Defining and then measuring liquidity is not trivial, 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

---

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

traders' funding liquidity, i.e., the ease with which market makers can obtain funding for their inventories of securities (Brunnermeier and Pedersen, 2008). 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.

We examine peer-group returns by regressing the peer-group benchmark monthly return $(r_{t,j}^{PG})$ 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):

$$r_{t,j}^{PG} = \alpha + \beta_1 Mkt_{j,t} + \beta_2 Mkt_{j,t-1} + \gamma_1 Liq_t + \gamma_2 Liq_{t-1} + \varepsilon_t. \tag{10}$$

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 $sMkt$) and $\gamma_1 + \gamma_2$ (denoted $sLiq$). Panel A of Table 4 presents the estimates and shows that the explanatory power of this simple model is very high, except for cash/alternatives.[23] We find that the exposure to market risk $(sMkt)$ is roughly equal to unity for UK and international equities as well as for property. This will only be the case if the average fund has approximately the same individual security weightings in each asset class as the underlying market index for that 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

---

[23]Note that we focus on the 1995-2012 period, rather than the full 1987-2012 period for a number of reasons. First, 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). By restricting the analysis to the period after 1995, we can work with a more homogeneous data sample which allows us to derive more precise estimates of pension funds' exposures. The second reason is more practical. The number of funds in our dataset grew rapidly in the early years and only stabilized after 1993. This consideration is important especially in light of our goal to identify size and sector type effects with high precision. However, our results are qualitatively similar when using the full sample.

is 0.68, hence well below unity; the most likely explanation for this is that the average fund's weightings in its international bond portfolio diverges significantly from the external index weightings.[24]

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. The liquidity exposures are negative for UK index-linked bonds and for property returns, suggesting that these asset classes help to hedge against liquidity risk, as they perform well at times of low global liquidity. The regressions for the period 2008-12 (covering the global financial crisis and its aftermath) 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.[25,26]

5.2   Factors Driving Pension Fund Net Investment

In this section, we investigate pension fund rebalancing in more detail. 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

---

[24]The main reason why a fund might not replicate an external index is a deliberate decision not to hold some of the securities covered by the index. For example, take an international bond index. This will be heavily weighted towards highly indebted countries. The fund might decide to underweight or possibly avoid altogether bonds from such countries in its own international bond portfolio. See Blake and Timmermann (2002) for further details on this issue.

[25]In the rest of the paper, we will use the term 'crisis period' to refer to the 2008-12 period covering the global financial crisis and its aftermath.

[26]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 specifically for the property market.

(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 return and net investment differentials ($\mathrm{corr}(r_t, ncf_t)$) 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 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. Panel B shows that the extent of rebalancing increased during the crisis period, with net investment being negative in all asset categories except cash/alternatives and property.[27]

We complement the analysis of Table 5 by regressing the flow component of changes in portfolio weights on the market and liquidity factors.[28] Specifically, we estimate:

$$\widetilde{NCF}_{j,t} \equiv ncf_{j,t} - ncf_{p,t} = \alpha + \sum_{s=0}^{3} \beta_s Mkt_{j,t-s} + \sum_{s=0}^{3} \gamma_s Liq_{j,t-s} + \varepsilon_t, \qquad (11)$$

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; $Mkt_{t-s,j}$ is the return on the external market index j at time $t - s$; and Liq_{t-s} is the time $t - s$ measure of liquidity, as described in

---

[27]In the Internet Appendix, we show 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.

[28]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.

Section 5.1.[29] Panel A of Table 6 reports the aggregate market ($sMkt=\sum\limits_{s=0}^{3}\beta_s$) and liquidity ($sLiq=\sum\limits_{s=0}^{3}\gamma_s Liq_{t-s}$) 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. 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 strategic asset allocation 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 liability driven investment. 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,

---

[29]Compared to the return regressions, we include more lags to account for the stronger persistence of flow effects. 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.

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.[30]

5.3   Summary of Results

The results in this section suggest that: i) the average pension fund returns are positively related to both market and, although to a lower extent, liquidity factors; and ii) pension funds rebalance their portfolios in response to valuation changes, implying that they buy into an asset class after a negative return and vice versa. This portfolio rebalancing mechanism occurs for both equities and (even more strongly) bonds, which are the two dominant components of pension funds' portfolios.[31]

6   Liquidity Premia

So far, we have investigated the response of the peer-group average pension fund's returns and return-adjusted weights to market and liquidity factors. Changes in the peer-group benchmark's portfolio weights over the longer term should largely respond to changes in pension fund liabilities, rather than to changes in the average fund manager's active management strategies. At the same time, the long-term nature of their liability structure and the stability of their cash outflows should allow pension funds to earn higher net returns by investing in illiquid securities and earn a liquidity premium from doing so. This type of investment behavior should also be beneficial from a financial stability perspective to the extent that it is less procyclical than alternative investment strategies (Papaioannou, Park, Phlman and van der Hoorn, 2013).

However, given differences in liability structures, there might be cross-sectional differences in the ability of pension funds to exploit liquidity effects. Despite our finding that the average fund does not display any active management ability – in terms of market timing and portfolio

---

[30]However, this could be influenced by the fact that our measure of liquidity does not properly reflect the actual liquidity conditions in the property market.

[31]In the Internet Appendix we provide further analysis which goes beyond peer-group returns and flow effects to allow also for the impact of size using double sorts. We find no strong effect of size on returns, and that large private-sector funds de-risked the most over the sample by switching from equities to bonds. However, the core results from this section remain the same.

selection skill – there are important cross-sectional differences in the funds' performance which might be related to different exposures to liquidity shocks. Also, we have found that pension funds appear to herd in subgroups and, in turn, these subgroups of funds may differ in their propensities to take on liquidity risk.

A related question is whether a liquidity premium is priced in the returns earned by the funds in excess of the peer-group return. In other words, do funds more exposed to liquidity effects generate higher active returns? Further, is the premium earned by riskier funds in 'normal' times sufficiently large to compensate for periods of low liquidity?

We employ the Fama and MacBeth (1973) procedure to address the above questions. Specifically, we group the funds into N equally-weighted portfolios according to their exposures to liquidity shocks, and then estimate the price of risk by relating the portfolios' average excess returns to risk exposures. If funds with greater risk exposure display higher expected returns, we can conclude that, e.g., liquidity risk is priced and hence rewarded in the pension funds' active management strategies.

We first separate portfolio returns into components arising from passive and active management. The total return on the portfolio can be approximately decomposed into the return from the passive strategic asset allocation, the return from portfolio selection and the return from market timing (e.g. Blake, Lehman and Timmermann, 1999). We focus on the return of the fund in excess of the peer-group return, thereby focusing on the active management component of the fund return, without looking separately at the selection and market timing components. However, we also repeat the analysis by replacing active returns with returns in excess of the risk-free rate. In this way, we can assess whether pension funds exploit the liquidity shortages of other investors.

6.1 Total Assets

We begin the analysis by considering the total value-weighted return and then turn to the individual asset classes. Let $r_{p,t}^n - r_{p,t}^{PG}$ be the month-t total return of pension fund n in excess of the benchmark return. Following Hu, Pan and Wang (2013), we estimate the exposure of

fund n to market and liquidity factors as:

$$r_{p,t}^n - r_{p,t}^{PG} = \alpha_n + \beta_n Mkt_t + \gamma_n Liq_t + \varepsilon_t, \tag{12}$$

where Mkt_t is the return on the world stock market at time t, and Liq_t is the time-t measure of liquidity.[32] For each month t and each pension fund n, we use the fund's return in excess of the benchmark return over the previous 24 months to estimate the pre-ranking exposure using eq. (12). Each month, the cross-section of pension funds is sorted by their pre-ranking exposure to γ_n into $N = 5$ value-weighted portfolios. The post-ranking betas and gammas of the N portfolios are estimated from the regression:

$$r_{p,t}^k - r_{p,t}^{PG} = \alpha_k + \beta_k Mkt_t + \gamma_k Liq_t + \varepsilon_t, \tag{13}$$

where $r_{p,t}^k$ is the month-t average value-weighted return of the funds included in portfolio k. We are interested in liquidity risk in the post-ranking portfolios. We denote as H the high-risk portfolio containing the quintile of funds most highly exposed to liquidity shocks, as reflected in the highest values of γ_k: when liquidity deteriorates, the high-risk portfolio return falls. We denote as L the low-risk portfolio that includes funds displaying a negative exposure to liquidity (i.e., they have negative values of γ_k, implying they are liquidity hedges). The estimated post-formation γ_k (not reported) increases monotonically as we move from the low- to the high-risk portfolio. Of particular interest is the spread portfolio (HML), long in H and short in L, with a return equal to the return on the high-risk portfolio minus the return on the low-risk portfolio. The top chart of Figure 7 shows the cumulative returns on the spread portfolio. It is apparent that funds most heavily exposed to liquidity risk outperform low-risk funds in the period up to 1999. This superior performance is partially reversed during the following three years. In fact, over the 1999-2002 period, the low-risk pension funds outperform the high-risk pension funds. Then during the so-called 'search for yield' period starting from

---

[32]We use the FTA World (ex-UK) index to proxy for the world stock market. However, the results are robust to using other standard world indices. Also, in contrast with Section 5.1 we do not include lagged market and liquidity factors. This is mainly because we now focus on returns in excess of the benchmark return so that the serial correlation problem is negligible. However, we also experimented with introducing lagged market and liquidity factors, and the results remain unchanged.

2002, the high-risk funds earn additional returns but, during the 2008-09 crisis, they perform substantially worse than the low-risk funds (by -12%). Over the full sample period, the funds most exposed to liquidity risk performed significantly worse than the funds that were least exposed, implying that overall the liquidity premium earned was not sufficient to compensate for the amount of liquidity risk assumed, most of which materialized during the crisis period.[33]

Finally, one may argue that, if the average fund were to invest in illiquid assets, this would be reflected in the peer-group returns so that it would not be captured by the active returns. As a result, based on the active returns we can only shed light on cross-sectional differences among pension funds, but we cannot conclude whether pension funds exploit the liquidity shortages of other investors. For this reason, we repeat the portfolio sort analysis on funds' returns in excess of the risk-free rate. We find that the results are largely unchanged: pension funds' average excess returns, regardless of the portfolio considered, are not different from zero.

6.2 International Equities

So far, we have not found evidence of liquidity premia being priced in the cross-section of pension fund returns. However, despite there not being evidence of liquidity premia at the fund level, pension funds might seek to exploit liquidity premia in particular asset classes. We therefore repeat the Fama and MacBeth (1973) procedure to investigate the funds' active management ability by asset class. We find evidence of a liquidity premium with international equities, but not for any other asset class. Therefore, we analyze in more detail the case of international equities below.

For each month t and each pension fund n, we use the fund's return over the previous 24 months to estimate the pre-ranking exposure using eq. (12). However, the dependent

---

[33]Examining the sector and size characteristics of the five portfolios in detail, we find that the lowest and highest risk portfolios are largely populated by private-sector funds (around 65 and 53 percent, respectively). Moreover, smaller funds are more exposed to liquidity risk: the highest-risk (lowest-risk) portfolio is largely populated by smaller (larger) funds. To be precise, the size of the average fund in the lowest risk portfolio is £1.2 billion, whereas the average fund size in the highest risk portfolio is £0.77 billion. The intervening portfolios display a monotonically inverse relationship between size and risk. For market risk, the funds exposed to greater risk (those with the highest β_k, conditional on having the highest pre-ranking γ_n exposure) should experience higher returns. However, we find that this prediction is not supported by the data. These results are not tabulated to economize on the space, but they are available upon request.

variable is now the difference between the pension fund's month-t return from investing in international equities, $r^n_{ie,t}$, and the international equities peer-group return, $r^{PG}_{ie,t}$. The month-t cross-section of pension funds is sorted by their pre-ranking exposure to liquidity risk (γ_k) into $N = 5$ portfolios. We then estimate the post-ranking γ_k of the five portfolios, reported in Panel A of Table 7. The lowest-risk (highest-risk) portfolio displays a negative (positive) γ_k, so that it includes funds that overperform (underperform) at times of decreasing liquidity. The post-ranking liquidity exposures are estimated with increasing precision as we move away from the central portfolios towards the corner portfolios. Moreover, the portfolios' exposure to liquidity risk exhibits a monotonic relationship with the portfolios' return rankings.

The lowest-risk portfolio underperforms the benchmark return on average, displaying average annualized active returns of -44 basis points per year, whereas the highest-risk portfolio outperforms the benchmark by 50 basis points on average per year. This results in average returns of 94 basis points per annum for a spread portfolio that is long the highest-risk and short in the lowest-risk portfolios.[34] The cumulative returns on this spread (*HML*) portfolio are displayed in Panel B of Figure 7. It is apparent that, apart from a few exceptions, such as the 1997-98 Asian and Russian financial crises, the highest risk portfolio generates higher returns than the lowest risk portfolio. This higher performance is evident also in the build-up to the 2008-09 financial crisis. During the crisis, the *HML* portfolio experiences a substantial loss, although over the whole sample it generates an excess return of 23 percent. In sum, these results do indeed suggest the existence of a risk-return relationship, whereby riskier international equity funds are associated with higher expected returns.

Next, we test more formally this hypothesis. Following Cochrane (2005), we estimate the factor risk premia λ from a cross-sectional regression across portfolios of average returns on market and liquidity exposures:

$$E\left[rx^k\right] = \widehat{\beta}_k \lambda^M + \widehat{\gamma}_k \lambda^L + \varepsilon^k \tag{14}$$

---

[34]Panel A of Table 7 also reports the return in excess of the risk-free rate (LIBOR). Despite these returns being substantially higher than the returns in excess of the benchmark return, they are not different from zero. This possibly reflects the fact that returns in excess of the risk-free rate display a much higher volatility than the active returns.

where $E\left[rx^k\right]$ denotes the average return of portfolio k in excess of the benchmark return, and $\widehat{\beta}_k$ and $\widehat{\gamma}_k$ are the post-formation portfolios' market and liquidity exposures, respectively, as presented in Panel A of Table 7. The estimated factor risk price λ and the cross-sectional adjusted R^2s are presented in Panel B of Table 7. To account for the fact that betas are estimated, we report t-statistics based on the Shanken (1992) adjustment. We find that liquidity risk is indeed priced in the case of international equities. The coefficient that corresponds to the liquidity risk premium is positive (0.57) and statistically significant (with a 1.92 t-statistic). In contrast, the market risk premium is not statistically different from zero. The adjusted R^2 is 0.97, which is in line with other studies performing asset pricing tests using five portfolios (e.g., Menkhoff, Sarno, Schmeling and Schrimpf, 2012). The findings of Panel B corroborate the intuition that the riskiest portfolios offer a positive risk premium. We then implement the χ^2 test for zero pricing errors and cannot reject the null that the pricing errors are zero, therefore providing further evidence in favor of the validity of this pricing model.[35]

6.3   Summary of Results

The results in this section, taken together, show i) the lack of cross-sectional differences in funds' ability to extract liquidity premia, and ii) the inability of funds' to exploit the liquidity shortages of other investors. Both results are consistent with our earlier results, highlighting the propensity of pension funds' to herd around the average fund which, in turn, is an index matcher, and therefore invests in highly liquid securities. As a result, we can conclude that over the past 25 years, UK pension funds' did not act as liquidity providers, in contrast with what one might expect from long-term investors, and therefore failed to play a useful role in helping stabilize financial markets.

---

[35]That is, there are no excess returns left unexplained: asset prices are fully explained by the included (market and liquidity) pricing factors. Note also that we do not find significant differences in the characteristics of the funds populating the different portfolios. In particular, we do not find the negative relationship between fund size and liquidity exposure that we documented in the case of total assets. Note also that we do not include a constant in the cross-sectional regression, which can be run with or without a constant (Cochrane, 2005). By imposing the null, we resolve the trade-off in favor of efficiency over robustness.

7 Concluding Remarks

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. As a result, institutional investors' behavior can exacerbate asset price movements and affect the stability of financial markets. Of particular interest are pension funds. Globally, they are as large as mutual funds, but much less is known about their investment behavior. This is largely due to the scarcity of data. In this paper, we use a unique dataset on the UK pension funds' monthly allocations to major asset classes over the period 1987-2012. This data sample covers around one third (by value) of the UK pension fund industry as of 2012, and allows us to investigate the behavior of private- and public-sector funds over the past 25 years.

We find strong evidence that pension funds herd and, in particular, they herd in subgroups defined by size and sector type, consistent with reputational herding. The impact of pension funds could clearly be destabilizing if they were also to follow positive-feedback strategies such as momentum trading but we do not find evidence that they do. However, we find that pension funds rebalance their portfolios in a way that is consistent with meeting their mandate restrictions in the short term, and with maintaining a long-term strategic asset allocation that matches the maturity of their liabilities. This mechanical rebalancing could also be destabilizing if it has the effect of driving prices away rather than towards equilibrium values.

Finally, the long-term nature of their liabilities and their predictable cash outflows should allow pension funds to earn higher net investment returns by investing in illiquid securities. We find that pension funds differ in their exposures to illiquidity depending on their size and sector type. However, over the full sample, we find no evidence of liquidity premia being priced in the cross-section of pension funds' total returns in excess of the peer-group return which, in turn, is very similar to the market return as measured by external indices. Turning to the individual asset classes, we only find evidence of a liquidity premium being priced in the cross-section of pension fund returns resulting from their investment in international equities.

The bottom line is that, although they are long-term investors, UK pension funds have not earned a positive long-run liquidity premium on their investments derived from exploiting the liquidity shortages of other investors. In other words, they have not made best use of a key comparative advantage as long-term investors. This is likely because their investment behavior is driven by different incentives. Pension fund managers fear relative underperformance against their peer-group, which encourages them in the very short term to herd around the average fund manager, who turns out to be a closet index matcher. Further, their short-term objective is to rebalance their portfolios when valuation changes across different asset classes lead to portfolio weights that violate investment mandate restrictions, while their long-term objective is to systematically switch from equities to bonds as their liabilities mature. Overall, our results show that pension fund investment behavior might be less stabilizing than previously believed.

A Appendix: A Closer Look at Reputational Herding

In this section, we describe the reputational herding tests implemented in Section 4.2.2, where we adapt the tests developed by Sias (2004) and Choi and Sias (2009) by grouping 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 new 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:

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

$$\text{Avg different-size}_t^{\text{Small}} = \frac{1}{J}\sum_{j=1}^{J}\left[\sum_{n=1}^{C_{j,t}}\sum_{m=1,m\neq n}^{MB_{j,t-1}}\left(\frac{D_{n,j,t}-\overline{RawW\Delta_t}}{C_{j,t}}\frac{D_{m,j,t-1}-\overline{RawW\Delta_{t-1}}}{ML_{j,t-1}}\right)\right],$$
(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: Double Sort. We perform a 3×2 double sort in which we classify funds into terciles according to their size (small, medium, large) and sector

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:

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

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

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:

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

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

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:

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

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

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

Defining and therefore measuring liquidity is not trivial, and there is no single measure that can capture its full complexity. According to Kyle (1985), market liquidity is a slippery and elusive concept, that it encompasses a number of transactional properties of markets, such as tightness, depth and resilience. Moreover, market liquidity is closely connected with funding liquidity (Brunnermeier and Pedersen, 2008). For this reason, we try to capture such complexity by aggregating several commonly used measures of liquidity. Specifically, we take 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 to Hu, Pan and Wang (2013) for more details on the construction of the noise measure.

References

ANDONOV, A., R. BAUER, AND M. CREMERS, 2012, Can Large Pension Funds Beat the Market? Asset Allocation, Market Timing, Security Selection, and the Limits of Liquidity, mimeo, Maastricht University.

ANDONOV, A., R. BAUER, AND M. CREMERS, 2013, Pension Fund Asset Allocation and Liability Discount Rates: Camouflage and Reckless Risk Taking by U.S. Public Plans? mimeo, Maastricht University.

BACCHETTA, P., C. TILLE, AND E. VAN WINCOOP, 2012, Self-Fulfilling Risk Panics, *American Economic Review* 102, 3674–3700.

BANERJEE, A., 1992, A Simple Model of Herd Behavior, *American Economic Review* 88, 724-48.

BANK OF ENGLAND, 2014, Procyclicality and structural trends in investment allocation by insurance companies and pension funds, *A Discussion Paper by the Bank of England and the Procyclicality Working Group.*

BENZONI, L., P. COLLIN-DUFRESNE, AND R. S. GOLDSTEIN, 2007, Portfolio Choice over the Life-Cycle when the Stock and Labor Markets are Cointegrated, *Journal of Finance* 62, 2123-67.

BLAKE, D., 2003, *Pension Schemes and Pension Funds in the United Kingdom*, Oxford University Press, Oxford.

BLAKE, D., B. N. LEHMANN, AND A. TIMMERMANN, 1999, Asset Allocation Dynamics and Pension Fund Performance, *Journal of Business* 72, 429-61.

BLAKE, D., G. A. ROSSI, A. TIMMERMANN, I. TONKS, AND R. WERMERS, 2013, Decentralized Investment Management: Evidence from the Pension Fund Industry, *Journal of Finance* 68, 1133-77.

BLAKE, D., AND A. TIMMERMANN, 2002, Performance Benchmarks for Institutional Investors: Measuring, Monitoring and Modifying Investment Behaviour, in John Knight and Stephen Satchell (eds) *Performance Measurement in Finance: Firms, Funds and Managers*, Butterworth Heinemann, Oxford, 108-141.

BIKHCHANDANI, S., D. HIRSHLEIFER, AND I. WELCH, 1992, A Theory of Fads, Fashion, Custom, and Cultural Change as Informational Cascades, *Journal of Political Economy* 100, 992-1026.

BRUNNERMEIER, M. K., 2009, Deciphering the Liquidity and Credit Crunch 2007–2008, *Journal of Economic Perspectives* 23, 77–100.

BRUNNERMEIER, M., AND L. H. PEDERSEN, 2009, Market Liquidity and Funding Liquidity, *Review of Financial Studies* 22, 2201-38.

CHAN, L. K. C., AND J. LAKONISHOK, 1995, The Behavior of Stock Prices Around Institutional Trades, *Journal of Finance* 50, 1147-1174.

CHEN, J., H. HONG, M. HUANG, AND J. D. KUBIK, 2004, Does Fund Size Erode Mutual Fund Performance? The Role of Liquidity and Organization, *American Economic Review* 94, 1276-1302.

CHOI, N., AND R. SIAS, 2009, Institutional Industry Herding. *Journal of Financial Economics* 94(3), 469-491.

COCHRANE, J. H., 2005, *Asset Pricing* (Revised Edition), Princeton University Press, NJ.

COHEN, N., 2014, US Public Pensions Ignore the Elephant in the Room, *Financial Times*, 2 March.

FAMA, E. F., AND J. D. MACBETH, 1973, Risk, Return, and Equilibrium: Empirical Tests, *Journal of Political Economy* 81(3), 607-636.

FEROLI, M., A. KASHYAP, K. SCHOENHOLTZ, AND H. S. SHIN, 2014, Market Tantrums and Monetary Policy, Report for the 2014 US Monetary Policy Forum.

FISHER, J. D., D. GELTNER, AND H. POLLAKOWSKI, 2007, A Quarterly Transactions-Based Index of Institutional Real Estate Investment Performance and Movements in Supply and Demand. *Journal of Real Estate Finance and Economics* 34(1), 5-33.

FROOT, K. A., D. S. SCHARFSTEIN, AND J. C. STEIN, 1992, Herd on the Street: Informational Inefficiencies in a Market with Short-term Speculation, *Journal of Finance* 47, 1461-84.

GREENWOOD, R., AND D. VAYANOS, 2010, Price Pressure in the Government Bond Market, *American Economic Review P&P* 100(2), 585-90.

GRINBLATT, M., AND S. TITMAN, 1989, Portfolio Performance Evaluation: Old Issues and New Insights, *Review of Financial Studies* 2, 393-422.

GRINBLATT, M., AND S. TITMAN, 1993, Performance Measurement without Benchmarks: An Examination of Mutual Fund Returns, *Journal of Business* 66, 47-68.

GRINBLATT, M., S. TITMAN, AND R. WERMERS, 1995, Momentum Investment Strategies, Portfolio Performance, and Herding: A Study of Mutual Fund Behavior, *American Economic Review* 85, 1088-1105.

HALDANE, G. A., 2014, The Age of Asset Management? Speech given at the London Business School (4 April).

HU, X., J. PAN, AND J. WANG, 2013, Noise as Information for Illiquidity, *Journal of Finance* 68, 2223-72.

KYLE, A. S., 1985, Continuous Auctions and Insider Trading, *Econometrica* 53(6), 1315-35.

LAKONISHOK, J., A. SHLEIFER, AND R. W. VISHNY, 1992, The Impact of Institutional Trading on Stock Prices, *Journal of Financial Economics* 32, 23-43.

LUCAS, D. J., AND S. ZELDES, 2009, How Should Public Pension Funds Invest?, *American Economic Review* P&P 99, 527-532.

MENKHOFF, L., L. SARNO, M. SCHMELING, AND A. SCHRIMPF, 2012, Carry Trades and Global Foreign Exchange Volatility, *Journal of Finance* 67, 681-718.

Nofsinger, J., and R. Sias, 1999, Herding and Feedback Trading by Institutional and Individual Investors, *Journal of Finance* 54, 2263-2295.

Papaioannou, M. G., J. Park, J. Pihlman, and H. van der Hoorn, 2013, Procyclical Behavior of Institutional Investors During the Recent Financial Crisis: Causes, Impacts and Challenges, IMF Working Paper 193.

Pástor, L., and R. F. Stambaugh, 2003, Liquidity Risk and Expected Stock Returns, *Journal of Political Economy* 111, 642-85.

Rajan, R. G., 2006, Benign Financial Conditions, Asset Management, and Political Risks: Trying to Make Sense of Our Times, Speech at the *Conference on International Financial Instability: Cross-Border Banking and National Regulation*, Federal Reserve Bank of Chicago, October 5-6, 2006.

Scharfstein, D. S., and J. C. Stein, 1990, Herd Behavior and Investment, *American Economic Review* 80, 465-479.

Sias, R., 2004, Institutional Herding, *Review of Financial Studies* 17(1), 165-206.

Sias, R.W., Starks, L., and S. Titman, 2006, Changes in Institutional Ownership and Stock Returns: Assessment and Methodology, *Journal of Business* 79, 2869-2910.

Shanken, J., 1992, On the estimation of beta pricing models, *Review of Financial Studies* 5, 1-34.

Sundersan, S., and F. Zapatero, 1997, Valuation, Optimal Asset Allocation and Retirement Incentives for Pension Plans, *Review of Financial Studies* 10, 631-60.

Timmermann, A., and D. Blake, 2005, International Asset Allocation with Time-Varying Investment Opportunities, *Journal of Business* 78, 71-98.

Tonks, I., 2005, Performance Persistence of Pension Fund Managers, *Journal of Business* 78, 1917-42.

Wermers, R., 1999, Mutual Fund Trading and the Impact on Stock Prices, *Journal of Finance* 54, 581-622.

Wermers, R., 2000, Mutual Fund Performance: An Empirical Decomposition into Stock-Picking Talent, Style, Transaction Costs, and Expenses, *Journal of Finance* 55, 1655-95.

Table 1: **Summary Statistics: UK Pension Fund Returns**

	Mean	Med.	St.D.	Skew.	Kurt.	ρ_1	ρ_2	nobs
	Panel A: All Pension Funds							
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)							
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)							
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**

	avg(β_t)	$\overline{\beta_t^m}$	$\overline{\beta_t^h}$	$\overline{\beta_t^h} - \overline{\beta_t^m}$
	Panel A: Cash Flows			
[1]	0.4392	0.0293	0.4100	0.3807
	[1.626]	[21.719]	[21.528]	[20.086]
[2]	0.4717	0.0359	0.4358	0.3999
	[1.744]	[20.954]	[21.976]	[20.208]
	Panel B: Return-adjusted weights			
[1]	0.5511	0.0257	0.5254	0.4997
	[2.325]	[20.714]	[28.760]	[26.990]
[2]	0.5314	0.0397	0.4917	0.4520
	[2.201]	[21.913]	[23.514]	[21.003]

The table reports in Panel A the average β_t and the average t-statistics 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 Section 4. The time t correlation β_t is then decomposed as $\beta_t = \rho\left(\Delta_{j,t}, \Delta_{j,t-1}\right) = \beta_t^m + \beta_t^h$, as in eq. (4), where β_t^m indicates pension funds 'following their mandate' into and out of the same asset class, and β_t^h indicates pension funds 'following others' (herding). We report the sample average $\overline{\beta_t^m}$ and $\overline{\beta_t^h}$ with the relative time series t-statistics. 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). t-statistics are reported in square brackets. The data cover the period January 1987 - December 2012.

Table 3: **Reputational Herding: Decomposition by Sector Type and Fund Size**

	[1] All assets			[2] All assets ex CA		
	Panel A: Following others by sector type					
	C	LA		C	LA	
Same	0.0052	0.0039		0.0057	0.0025	
	[19.761]	[10.624]		[21.160]	[6.720]	
Other	0.0042	0.0049		0.0028	0.0054	
	[10.117]	[20.890]		[6.581]	[22.589]	
Diff.	0.0010	−0.0010		0.0030	−0.0029	
	[3.061]	[-3.608]		[8.067]	[-8.606]	
	Panel B: Following others by size					
	Large	Med.	Small	Large	Med.	Small
Same	0.0064	0.0092	0.0102	0.0066	0.0075	0.0090
	[18.383]	[16.610]	[19.849]	[17.826]	[14.348]	[16.866]
Other	0.0050	0.0070	0.0072	0.0037	0.0057	0.0060
	[12.569]	[17.171]	[17.964]	[9.398]	[14.127]	[15.436]
Diff.	0.0015	0.0022	0.0029	0.0029	0.0018	0.0029
	[4.441]	[6.236]	[7.603]	[7.578]	[5.366]	[7.323]
	Panel C: Following others by sector type, controlling for size					
	LarC	MedC	SmaC	LarC	MedC	SmaC
Same	0.0109	0.0056	0.0080	0.0142	0.0059	0.0070
	[21.922]	[6.672]	[15.045]	[22.702]	[6.526]	[12.689]
Other	0.0016	0.0045	0.0103	0.0010	0.0031	0.0089
	[2.959]	[5.748]	[13.928]	[1.775]	[4.211]	[11.495]
Diff.	0.0093	0.0010	−0.0023	0.0132	0.0028	−0.0019
	[13.750]	[1.099]	[-3.430]	[16.260]	[2.784]	[-2.771]
	LarLA	MedLA	SmaLA	LarLA	MedLA	SmaLA
Same	0.0099	0.0126	0.0139	0.0081	0.0105	0.0129
	[17.264]	[19.451]	[15.528]	[14.643]	[16.764]	[13.782]
Other	0.0025	0.0044	0.0100	0.0016	0.0028	0.0083
	[4.442]	[5.824]	[12.819]	[2.716]	[3.745]	[10.631]
Diff.	0.0073	0.0082	0.0039	0.0065	0.0077	0.0045
	[11.442]	[10.137]	[4.493]	[9.565]	[9.489]	[5.085]

The table reports the decomposition of a measure of reputational herding whereby pension funds 'following others' is decomposed into pension funds following other of *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)]. Panel A focuses on the sector 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. Panel C focuses on the sector type effect, controlling for size. 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 sector 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 sector type* [see eq. (A.5)]. 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 (ex CA), focusing on the remaining six asset classes. All t-statistics (reported in parenthesis) are computed from time-series standard errors.

Table 4: **Regressions of Peer-Group Benchmark Returns on Market Returns and Liquidity**

	Con	Mkt_t	Mkt_{t-1}	Liq_t	Liq_{t-1}	$sMkt$	$sLiq$	R^2
				Panel A: 1995-2012				
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: 2008-2012				
	Con	Mkt_t	Mkt_{t-1}	Liq_t	Liq_{t-1}	$sMkt$	$sLiq$	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). $sMkt$ ($sLiq$) 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 global financial crisis and its aftermath 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. Con is the constant term in the regression, 'CA' refers to cash/alternatives and 'UK IL' refers to UK index-linked bonds.

Table 5: **Evolution of Aggregate Portfolio Weights**

	Tot. Eq.	UK Eq.	Int. Eq.	Tot. Bo.	UK Bo.	Int. Bo.	UK IL	CA	Prop.
				Panel A: 1995-2012					
$\Delta \log(\omega_{jt})$	-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
$\mathrm{corr}(r, ncf)$	-0.32	-0.33	-0.10	-0.25	-0.18	-0.22	-0.16	-0.20	-0.04
% $\mathrm{var}(r)$	83.30	76.66	91.01	70.41	72.90	38.32	84.52	38.43	95.42
% $\mathrm{cov}(r, ncf)$	12.24	15.78	4.23	15.77	11.80	18.14	8.05	16.85	1.53
% $\mathrm{var}(ncf)$	4.47	7.55	4.76	13.83	15.30	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	1.40	1.33	0.57	0.71	4.63	-0.13
$r_{jt} - r_{pt}$	0.50	0.65	0.73	2.82	2.58	3.57	3.04	-3.20	-5.71
$ncf_{jt} - ncf_{pt}$	-2.03	-5.04	-0.96	-1.42	-1.25	-3.00	-2.33	7.83	5.58
$\mathrm{corr}(r, ncf)$	-0.40	-0.38	-0.21	-0.42	-0.41	-0.30	-0.19	-0.54	0.18
% $\mathrm{var}(r)$	84.71	78.20	89.51	74.48	76.25	44.18	85.81	48.52	92.11
% $\mathrm{cov}(r, ncf)$	12.41	16.16	7.24	18.79	17.74	22.94	8.40	32.51	5.39
% $\mathrm{var}(ncf)$	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 $\mathrm{var}(\Delta \log(\omega_{j,t})) \simeq \mathrm{var}(r_{j,t} - r_{p,t}) + \mathrm{var}(ncf_{j,t} - ncf_{p,t}) + 2\mathrm{cov}(r_{j,t} - r_{p,t}, ncf_{j,t} - ncf_{p,t})$. 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**

	Con	Mkt_t	Mkt_{t-1}	Mkt_{t-2}	Mkt_{t-3}	Liq_t	Liq_{t-1}	Liq_{t-2}	Liq_{t-3}	$sMkt$	$sLiq$	R^2
					Panel A: 1995-2012							
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
UK IL	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: 2008-2012							
	Con	Mkt_t	Mkt_{t-1}	Mkt_{t-2}	Mkt_{t-3}	Liq_t	Liq_{t-1}	Liq_{t-2}	Liq_{t-3}	$sMkt$	$sLiq$	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
UK IL	-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 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). $sMkt$ ($sLiq$) 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 the Newey-West standard errors. a, b, and c denote the 1-, 5-, and 10-percent significance levels, respectively. Con is the constant term in the regression, CA refers to cash/alternatives and UK IL refers to UK index-linked bonds.

Table 7: **Liquidity-Sorted Porfolios: International Equities**

	[1] Active Returns						[2] Excess Returns					
	exret	acret	Con	Mkt	Liq	R^2	exret	acret	Con	Mkt	Liq	R^2
	(%)	(%)	(%)	β	γ	(%)	(%)	(%)	(%)	β	γ	(%)
L	2.46	−0.44	−0.39	−0.01	−0.53	5.57	2.46	−0.45	−4.09	0.93	1.74	94.70
	[0.76]	[-2.11]	[-1.96]	[-1.53]	[-2.15]		[0.76]	[-2.12]	[-4.83]	[54.97]	[3.55]	
2	2.85	−0.06	−0.06	0.00	−0.29	1.03	2.86	−0.04	−3.75	0.93	1.98	94.52
	[0.87]	[-0.38]	[-0.41]	[0.40]	[-2.09]		[0.88]	[-0.29]	[-4.32]	[57.62]	[3.96]	
3	3.00	0.10	0.09	0.00	−0.04	-0.65	3.00	0.09	−3.62	0.93	2.20	94.37
	[0.92]	[0.66]	[0.65]	[0.24]	[-0.31]		[0.91]	[0.62]	[-4.10]	[53.64]	[4.41]	
4	3.00	0.09	0.06	0.00	0.14	1.58	3.00	0.09	−3.64	0.94	2.41	94.07
	[0.91]	[0.63]	[0.41]	[1.31]	[0.97]		[0.91]	[0.58]	[-4.08]	[54.52]	[4.34]	
H	3.41	0.50	0.48	0.00	0.77	5.31	3.41	0.50	−3.22	0.93	3.04	93.77
	[1.03]	[2.06]	[2.06]	[0.26]	[2.47]		[1.03]	[2.06]	[-3.52]	[53.82]	[4.74]	
HML	0.95	0.95	0.87	0.01	1.30	8.13	0.95	0.95	0.88	0.09	1.30	8.18
	[2.53]	[2.53]	[2.44]	[1.01]	[2.58]		[2.53]	[2.53]	[2.45]	[1.01]	[2.59]	

Panel B: Factor Prices

	[1] Active Returns					[2] Excess Returns			
	Mkt	Liq	R^2	Test		Mkt	Liq	R^2	Test
	β	γ	(%)	χ^2		β	γ	(%)	χ^2
	19.61	0.57	92.76	1.81		1.58	0.65	88.61	2.45
	[0.94]	[1.92]		(0.61)		[0.45]	[2.05]		(0.49)

The table reports regressions of liquidity-sorted portfolios on market (Mkt) and liquidity factors (Liq). Let $r_{ie,t}^n$ be the month-t return of pension fund n investing in international equities and $r_{ie,t}^{PG}$ the peer-group benchmark return for international equities. We estimate fund n's exposure to liquidity from $r_{ie,t}^n r_{ie,t}^{PG} = \alpha_n + \beta_n Mkt_{ie,t} + \gamma_n Liq_t + \varepsilon_t$. The month-$t$ cross-section of pension fund returns is sorted by their pre-ranking gamma γ_n into 5 portfolios, where γ_n is estimated using 24 months of past data. In Panel A, the left tab (*Active returns*) presents the regressions of the post-ranking portfolios' monthly forward peer-group benchmark-adjusted returns on the market and liquidity effects: $r_{ie,t,t+1}^k - r_{ie,t,t+1}^{PG} = \alpha_k + \beta_k Mkt_{ie,t} + \gamma_k Liq_t + \varepsilon_t$, where *acret* denotes the annualized return in excess of the peer group return. The right tab (*Excess returns*) presents the results using excess returns, i.e., fund exposures are estimated by replacing the dependent variable $r_{ie,t}^n - r_{ie,t}^{PG}$ with $r_{ie,t}^n - rf_t$, with corresponding post-ranking regressions: $r_{ie,t,t+1}^k - rf_{t,t+1} = \alpha_k + \beta_k Mkt_{ie,t} + \gamma_k Liq_t + \varepsilon_t$, where *exret* denotes the annualized return in excess of the risk-free rate. Newey-West (1987) t-statistics are presented in square brackets. Panel B reports cross-sectional pricing results for a linear factor pricing model where the factors are the market (Mkt) and liquidity (Liq) effects. The dependent variables are the active or excess returns on 5 liquidity-sorted portfolios based on all funds. We present factor risk prices λ^M and λ^L, while the factor loadings are those presented in Panel A. In the left tab, rx^k denotes the return on portfolio k in excess of the benchmark return, whereas in the right tab, it denotes the return on portfolio k in excess of the risk-free rate. χ^2 is the test statistics that the weighted sum of the squared residuals is different from zero, and is distributed as a χ^2_{N-K} where N=5 and K=2. We report the p-value in squared brackets. To account for the fact that factor loadings are estimated, we report the t-statistics computed with the Shanken (1992) adjustment. R^2 denotes the adjusted R-squared. *Con* is the constant term in the regression.
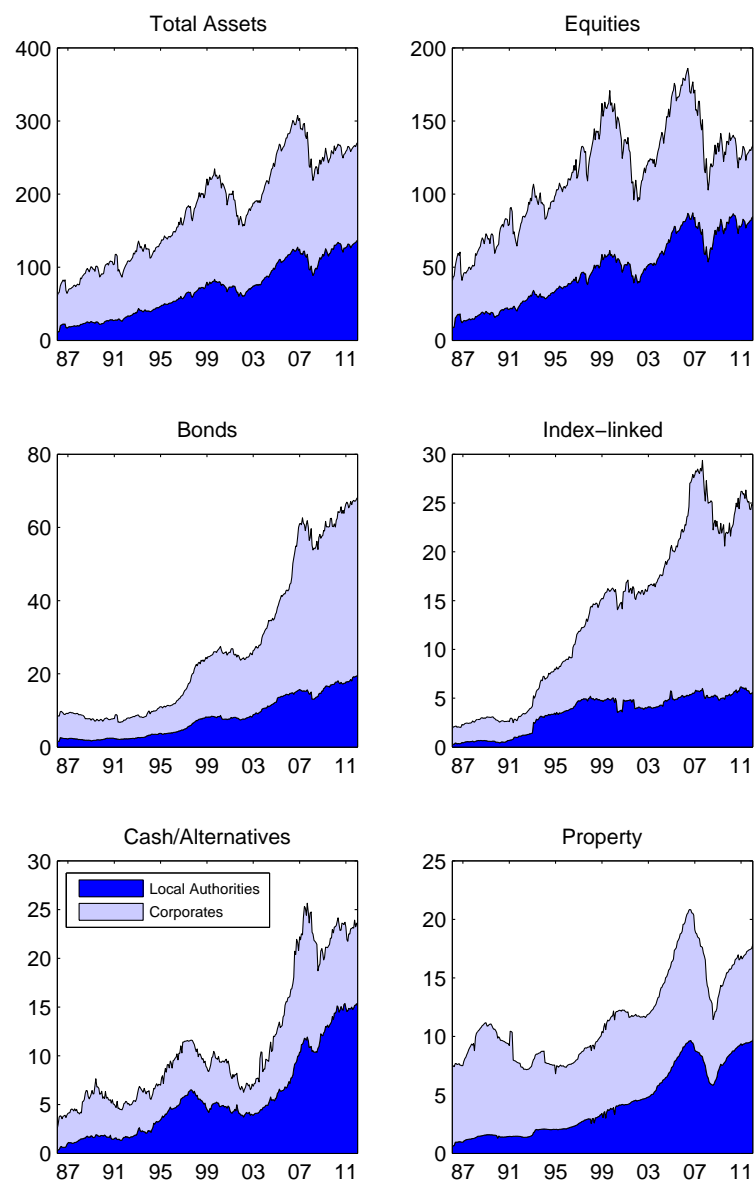
Figure 1: **UK pension fund asset holdings by sector type (in billion pounds)**
Note: The figure shows UK private- and public-sector funds' total asset holdings as well as their holdings in equities, bonds, UK inflation-linked bonds, cash/alternatives and property for the period from January 1987 to December 2012.

49
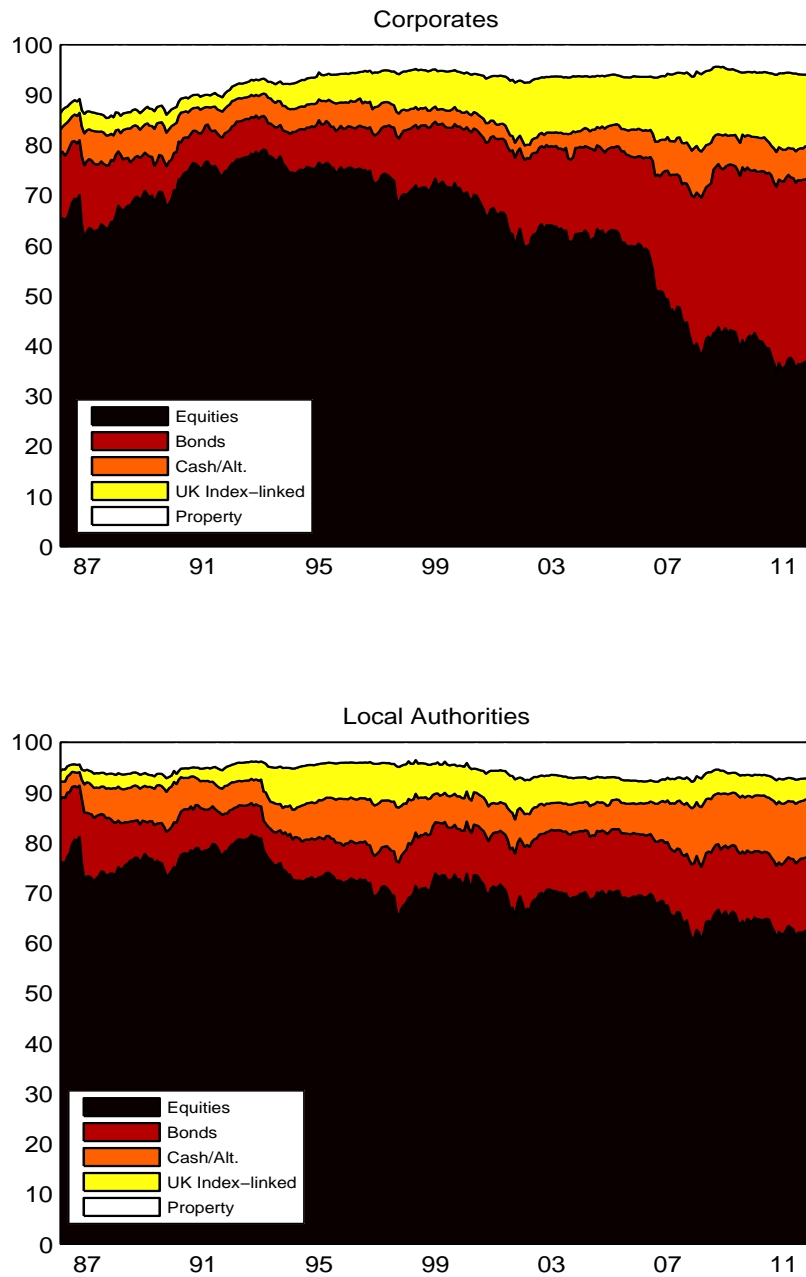
Figure 2: **Asset weights by sector type (in %)**
Note: The figure shows UK private- and public-sector funds' asset allocation weightings in equities, bonds, UK inflation-linked bonds, cash/alternatives and property for the period from January 1987 to December 2012.
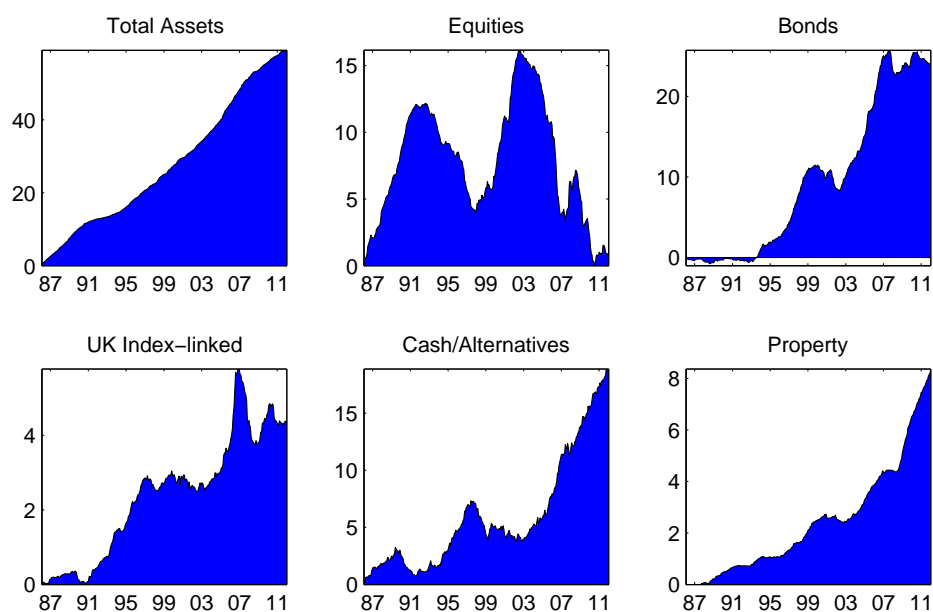
Figure 3: **Cumulative flows (in billion pounds)**

Note: The figure shows UK pension funds cumulative 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.
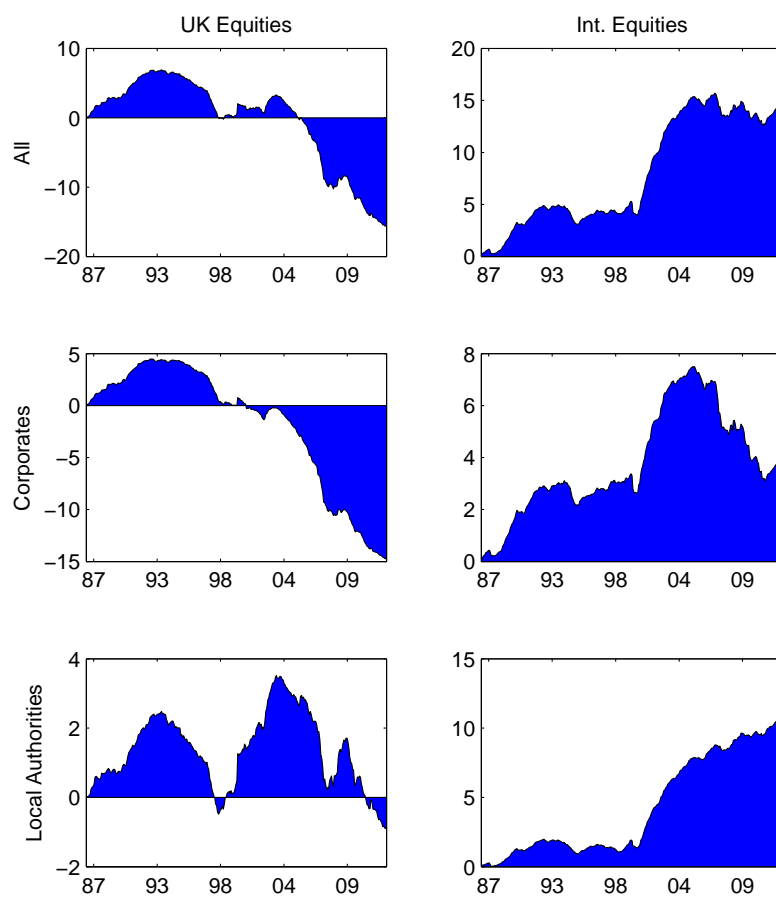
Figure 4: **Cumulative equity flows (in billion pounds)**
Note: The figure shows UK private- and public-sector cumulative flows (net investment) in total, UK and international equities for the period from January 1987 to December 2012.
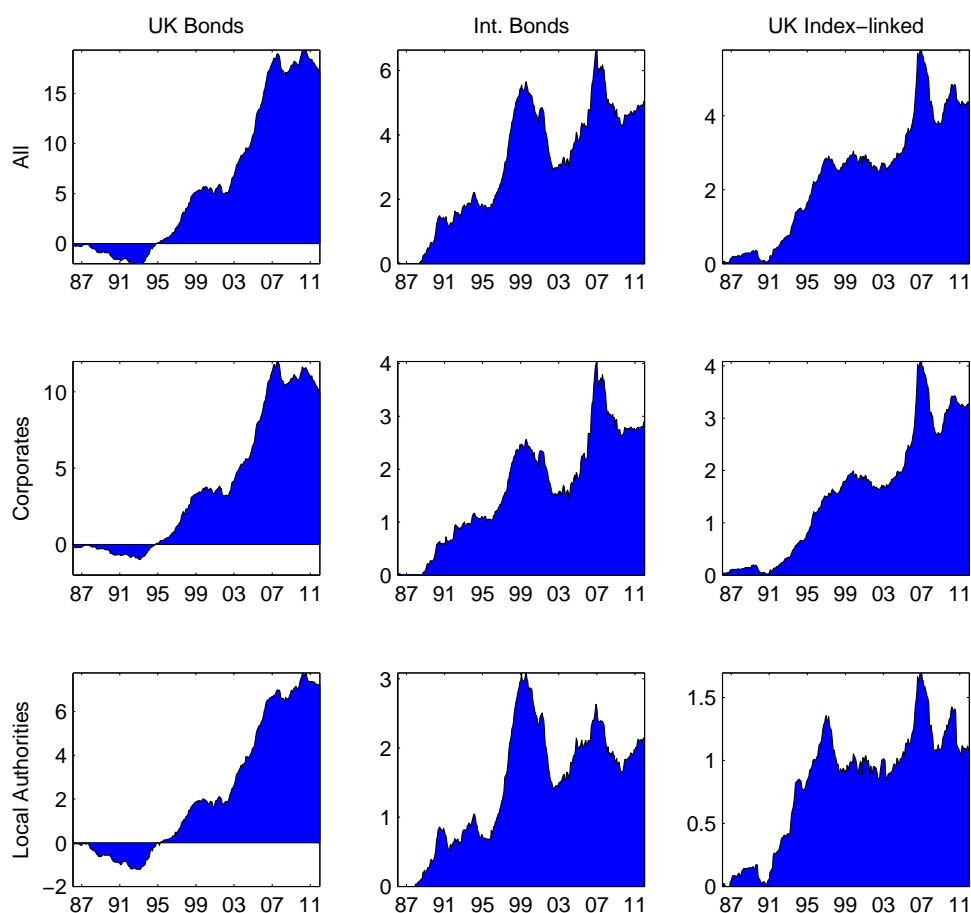
Figure 5: **Cumulative bond flows (in billion pounds)**
Note: The figure shows UK private- and public-sector cumulative flows (net investment) in UK and international fixed-income bonds and in UK index-linked bonds for the period from January 1987 to December 2012.
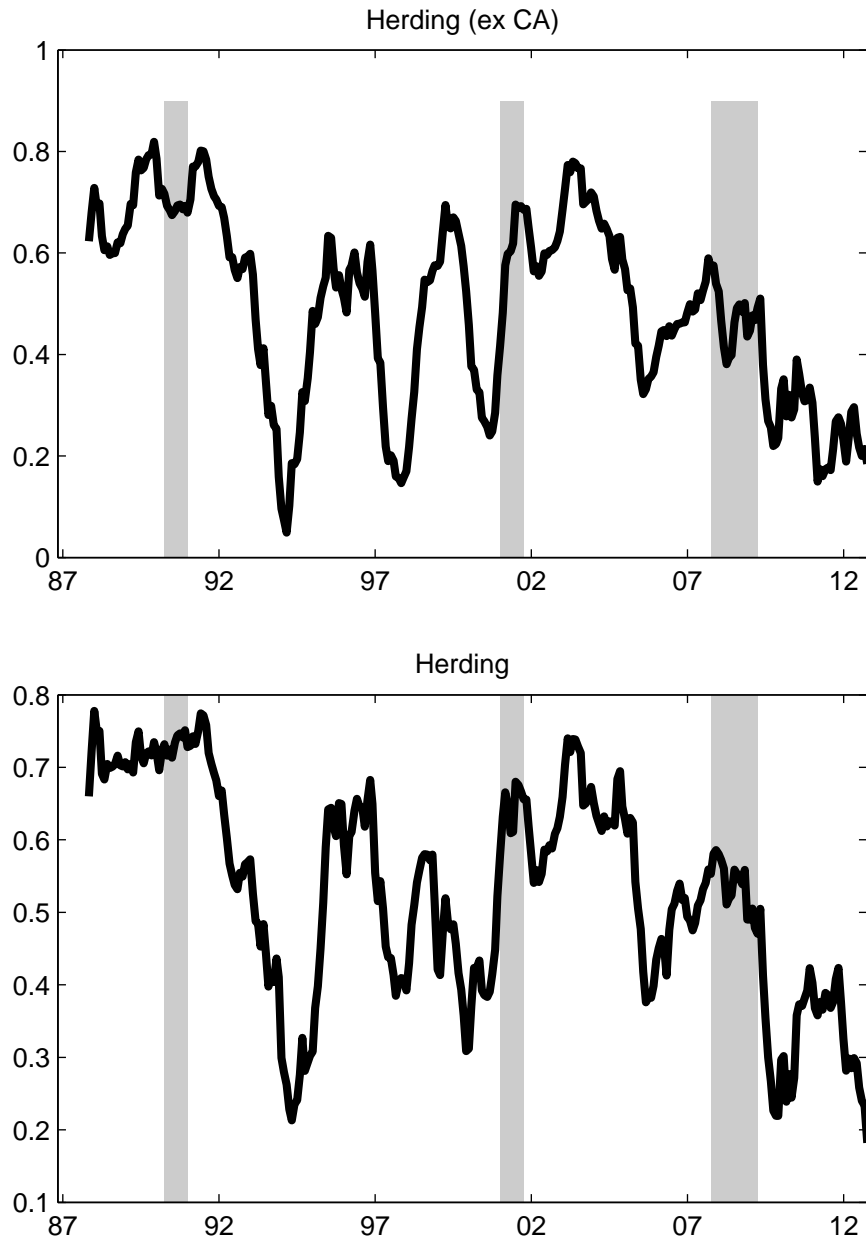
Figure 6: **Herding**

Note: The figure shows the 12-month moving average of the 'following others' (herding) component, as defined in eq. (4). The top panel shows the herding measure for total assets and the bottom panel shows the herding measure for total assets minus cash/alternatives. Shaded areas denote NBER recession dates.
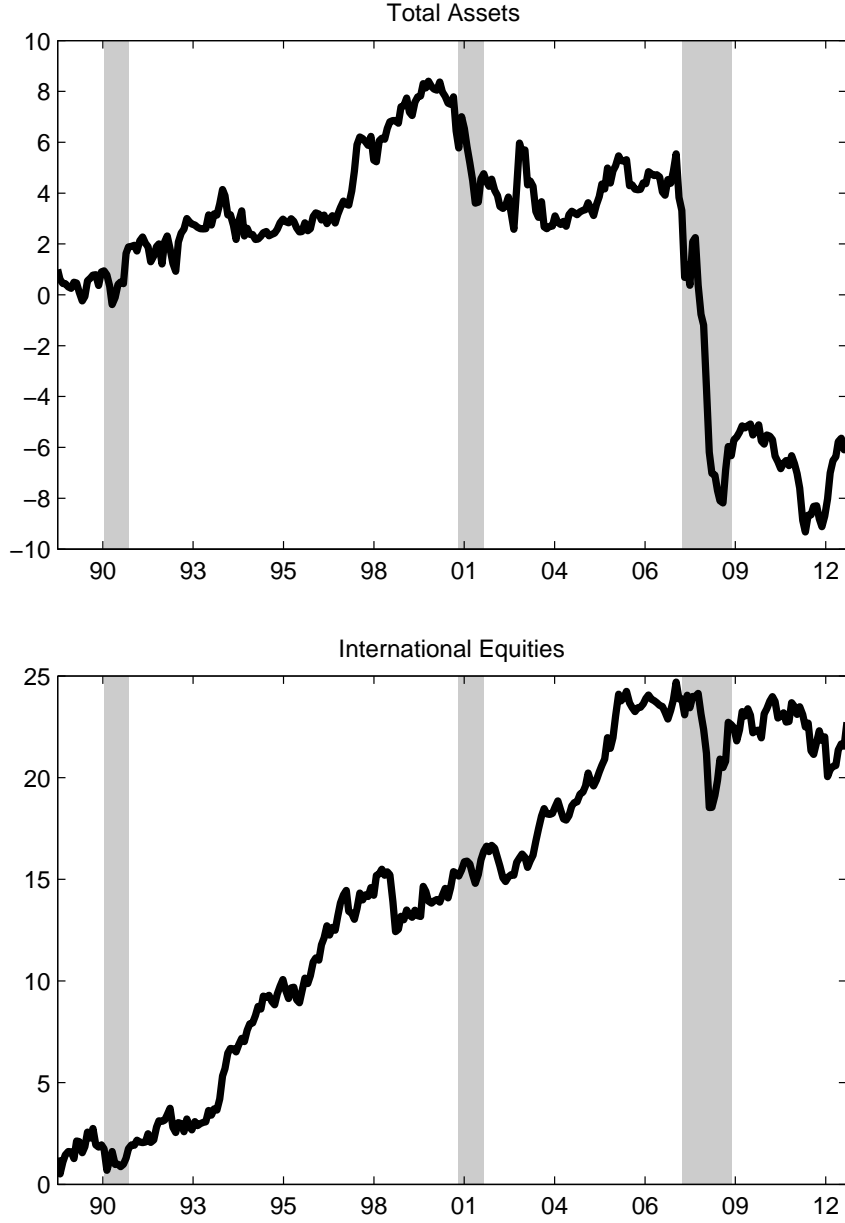
Figure 7: **Spread portfolio cumulative returns (in %)**

Note: The figure shows the cumulative sum of the spread portfolio returns. Let $r_{j,t}^n$ be the month t return of pension fund n from investing in asset class j and $r_{j,t}^{PG}$ the peer-group benchmark return for asset class j. We estimate fund n's exposure to liquidity as $r_{j,t}^n - r_{j,t}^{PG} = \alpha_n + \beta_n Mkt_{j,t} + \gamma_n Liq_t + \varepsilon_t$. $Mkt_{j,t}$ is the external benchmark for international equities. 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). The month t cross-section of pension fund returns is sorted by their pre-ranking γ_n into 5 portfolios, where γ_n is estimated using 24 months of past data. The *HML*, or spread portfolio, is long in the highest liquidity-risk portfolio and short in the lowest liquidity-risk portfolio. In the top panel, j denotes total assets, whereas in the bottom panel, j denotes international equities. Shaded areas denote NBER recession dates.

Internet Appendix
(not for publication)

The Market for Lemmings: Is the Investment Behaviour of Pension Funds Stabilizing or Destabilizing?

by
David Blake, Lucio Sarno and Gabriele Zinna

Table of Content Internet Appendix

I Additional Tables on Summary Statistics, Herding and Portfolio Rebalancing

Table A1: **Summary Statistics: Peer-group Benchmark Returns**

	Mean	Med.	St.D.	Skew.	Kurt.	ρ_1	ρ_2
Panel A: All Pension Funds							
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)							
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)							
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: **Reputational Herding: Following Others of Same Type and Size vs. All the Others**

	[1] All assets			[2] All assets ex CA		
	LarC	MedC	SmaC	LarC	MedC	SmaC
Same	0.0109	0.0056	0.0080	0.0142	0.0059	0.0070
	[21.922]	[6.672]	[15.045]	[22.702]	[6.526]	[12.689]
Other	0.0013	0.0051	0.0069	0.0007	0.0047	0.0056
	[2.831]	[9.494]	[16.614]	[1.580]	[9.267]	[14.073]
Diff.	0.0097	0.0005	0.0011	0.0135	0.0012	0.0013
	[15.093]	[0.578]	[2.395]	[17.592]	[1.475]	[2.677]
	LarLA	MedLA	SmaLA	LarLA	MedLA	SmaLA
Same	0.0099	0.0126	0.0139	0.0081	0.0105	0.0129
	[17.264]	[19.451]	[15.528]	[14.643]	[16.764]	[13.782]
Other	0.0076	0.0071	0.0087	0.0059	0.0054	0.0074
	[16.151]	[15.996]	[17.412]	[12.736]	[12.122]	[14.270]
Diff.	0.0022	0.0055	0.0052	0.0022	0.0051	0.0055
	[4.691]	[11.570]	[7.060]	[4.847]	[10.713]	[7.100]

The table compares the propensity of funds to follow other funds of different sector type when controlling for size. We sort funds according to their size and then for each tercile into corporates and local authorities. The analysis is based on the standardized fraction of pension funds increasing/decreasing the return-adjusted weight in j in month t. *Same* refers to the average contribution to the correlation from each pension fund following other pension funds of the same size and sector type [see eq. (A.3)]. *Other* refers to the average contribution to the correlation from each pension fund following pension funds other than pension funds of same size and sector type [see eq. (A.5)]. *Diff.* indicates the difference between *Same* and *Other*. Specification [1] includes the seven asset classes: UK equities, international equities, UK bonds, international bonds, UK index-linked bonds, property and cash/alternatives. Specification [2] excludes cash/alternatives focusing on the remaining six asset classes. All t-statistics (reported in parenthesis) are computed from time-series standard errors. The category *other* comprises all pension funds that are not of the same size or sector type. This table can be compared directly with Panel C in Table 3 in which *other* is restricted to funds of different sector type, but similar size.

Table A3: **Momentum Trading**

	Cash Flow		Adj. Weights	
	$\mathrm{avg}(\beta_{1,t})$	$\mathrm{avg}(\beta_{2,t})$	$\mathrm{avg}(\beta_{1,t})$	$\mathrm{avg}(\beta_{2,t})$
[1]	0.4296	-0.0418	0.5450	-0.0502
	[1.570]	[-0.200]	[2.215]	[-0.232]
[2]	0.4495	-0.0691	0.5029	-0.0697
	[1.699]	[-0.367]	[1.954]	[-0.291]

The table reports the average betas and 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 Flow), 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.

Table A4: **Evolution of Aggregate Weights by 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
$\mathrm{corr}(r, ncf)$	-0.18	-0.23	-0.06	-0.23	-0.16	-0.12	-0.02	-0.12	-0.15
$\% \, \mathrm{var}(r)$	84.09	75.03	89.56	65.56	69.35	16.89	70.67	20.20	84.75
$\% \, \mathrm{cov}(r, ncf)$	8.82	13.44	2.97	16.23	11.36	8.37	1.70	8.83	7.60
$\% \, \mathrm{var}(ncf)$	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
$\mathrm{corr}(r, ncf)$	-0.20	-0.30	-0.10	-0.41	-0.41	-0.23	-0.12	-0.43	0.11
$\% \, \mathrm{var}(r)$	85.98	76.24	87.53	66.43	67.69	24.06	81.02	28.39	91.95
$\% \, \mathrm{cov}(r, ncf)$	8.67	15.18	5.14	22.28	21.93	17.05	7.31	29.92	4.06
$\% \, \mathrm{var}(ncf)$	5.35	8.58	7.33	11.30	10.38	58.89	11.66	41.70	3.99
Panel B: Public Funds									
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
$\mathrm{corr}(r, ncf)$	-0.33	-0.40	-0.07	-0.17	-0.10	-0.19	-0.19	-0.22	0.01
$\% \, \mathrm{var}(r)$	81.43	73.65	89.92	66.67	57.11	42.05	78.28	34.74	94.79
$\% \, \mathrm{cov}(r, ncf)$	13.52	18.76	3.55	12.40	8.44	15.90	11.02	17.89	0.52
$\% \, \mathrm{var}(ncf)$	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
$\mathrm{corr}(r, ncf)$	-0.42	-0.40	-0.16	-0.36	-0.24	-0.27	-0.25	-0.47	0.11
$\% \, \mathrm{var}(r)$	83.05	74.82	91.61	78.29	82.71	55.57	78.55	59.73	92.83
$\% \, \mathrm{cov}(r, ncf)$	13.77	18.33	5.42	15.60	11.04	20.15	12.87	26.76	3.87
$\% \, \mathrm{var}(ncf)$	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 $\mathrm{var}(\Delta \log(\omega_{j,t})) \simeq \mathrm{var}(r_{j,t} - r_{p,t}) + \mathrm{var}(ncf_{j,t} - ncf_{p,t}) + 2\mathrm{cov}(r_{j,t} - r_{p,t}, ncf_{j,t} - ncf_{p,t})$. 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.

II Drivers of Portfolio Returns and Net Investment by Type and Size

II.1 Spread Portfolio Returns

The analysis in this section complements the results reported in Section 5. First, we go beyond peer-group returns and analyze spread portfolio returns where we also condition on size. Size is an important determinant of pension fund asset allocations. For example, BRTTW (2013) suggest that small funds are generally less well diversified than large funds. There might also be important differences between private- and public-sector funds, either linked to their differing liability structures (e.g., their maturity) or because public-sector funds, due to their implicit government guarantee in the UK, have a much stronger sponsor covenant and hence can take more risk. We therefore again perform a 3×2 double sort where we divide the funds into terciles according to their size (small, medium, large) and sector type (private, public), and construct equally weighted portfolios. However, we now focus on spread portfolios to highlight differences between private- and public-sector funds, controlling for size, and between funds of different size but of similar sector type. Specifically, we focus on four spread portfolios: the first portfolio (L/S LA) is long in large public-sector funds and short in small public-sector funds; the second (L/S C) is long in large private-sector funds and short in small private-sector funds; the third (LA/C L) is long in large public-sector funds and short in large private-sector funds; and the fourth (LA/C S) is long in small public-sector funds and short in small private-sector funds. Then we estimate:

$$r_{j,t}^a - r_{j,t}^b = \alpha + \beta_1 Mkt_{j,t} + \beta_2 Mkt_{j,t-1} + \gamma_1 Liq_{j,t} + \gamma_2 Liq_{j,t-1} + \varepsilon_t \tag{II.1}$$

where in the case of the L/S LA portfolio, for example, $r_{j,t}^a - r_{j,t}^b$ is the difference in returns between a portfolio of large public-sector funds and one of small public-sector funds for asset class j. The analysis of the differences in the risk-adjusted returns (α), denoted *Con* in Table A5, indicates that there is no systematically superior performance linked to size or sector type effects,[36] with the (fairly weak) exception of conventional bonds for both the whole period (Panel A) and the crisis period (Panel B). Over the whole period, large public-sector funds' risk-adjusted returns from investing in domestic bonds are higher than the returns generated by either small public-sector funds or large private-sector funds, while large private-sector funds generate higher relative risk-adjusted returns from investing in international bonds compared with small private-sector funds or large public-sector funds. These results weaken during the crisis period.

We now turn to the market and liquidity exposures of the spread portfolios. The results are mixed, although the largest market exposure differences occur in the bond portfolios. Small public-sector funds are more exposed than either large public-sector funds or small private-sector funds to market risk in these asset classes. Large private-sector funds are more exposed than small private-sector funds or large public-sector funds to market risk in domestic conventional bonds, but not in international bonds. Small funds are more exposed than large funds to liquidity shocks in all asset classes, except international bonds. Public-sector funds are more exposed to liquidity shocks than private-sector funds in equities, while the opposite holds for bonds. The higher exposure of small funds to liquidity effects may reflect their

---

[36]Instead, strong governance structures and a true long-term focus are likely to be much more meaningful drivers of long-term performance.

greater ability to trade smaller and less liquid stocks quickly. In contrast, larger funds face significant diseconomies of scale that limit their ability to move into and out of the more illiquid traded securities in size (Chen, Hong, Huang and Kubik, 2004; Andonov, Bauer and Cremers, 2012; BRTTW, 2013). Surprisingly, the impact of the liquidity effects is broadly unchanged during the crisis period.

Table A5: **Regressions of Spread Portfolio Returns on Market Returns and Liquidity, Decomposed by Sector Type and Fund Size**

		UK Equities				Int. Equities				UKIL		
	Con	$sMkt$	$sLiq$	R^2	Con	$sMkt$	$sLiq$	R^2	Con	$sMkt$	$sLiq$	R^2
L/S LA	0.00	0.01	-0.00	-0.22	0.02	-0.01	0.00	1.74	0.01	-0.02^b	-0.04^a	16.42
L/S C	-0.01	0.00	-0.00	1.48	-0.00	0.01^c	-0.09^a	11.32	0.01	0.01	-0.06^a	16.75
LA/C L	-0.00	0.00	0.03^a	4.02	0.02	-0.01^b	0.10^a	17.68	0.01	-0.02^a	0.01	7.12
LA/C S	-0.01	-0.00	0.03	5.39	0.00	0.01	0.01	-0.59	0.00	0.01	-0.01	-0.65
		UK Bonds				Int. Bonds				CA		
	Con	$sMkt$	$sLiq$	R^2	Con	$sMkt$	$sLiq$	R^2	Con	$sMkt$	$sLiq$	R^2
L/S LA	0.04^b	-0.08^a	-0.04^c	30.93	0.04	-0.12^a	0.15^b	45.81	0.07	-0.08	0.04	1.27
L/S C	-0.04	0.09^a	0.02	10.67	0.12^a	-0.04	-0.07^c	11.42	0.00	0.13	-0.14^a	11.09
LA/C L	0.04^b	-0.11^a	-0.04^b	24.43	-0.08^b	-0.04	0.02	16.01	-0.01	-0.04	0.04^c	3.78
LA/C S	-0.03^b	0.06^a	0.02	19.46	0.00	0.04	-0.20^b	17.54	-0.07	0.17	-0.14^a	17.19

Panel A: 1995-2012

Panel B: 2008-2012

		UK Equities				Int. Equities				UK IL		
	Con	$sMkt$	$sLiq$	R^2	Con	$sMkt$	$sLiq$	R^2	Con	$sMkt$	$sLiq$	R^2
L/S LA	0.01	0.02^a	-0.03^c	13.93	-0.00	0.01	-0.01	4.40	0.02	-0.04^b	-0.04^b	24.26
L/S C	-0.01	0.00	0.01	-5.22	-0.00	0.02^b	-0.10^a	13.02	0.02	0.02	-0.08^a	24.31
LA/C L	0.02	0.01^b	0.00	33.73	0.03	-0.01	0.10^a	28.76	-0.01	-0.04^b	0.03^c	9.81
LA/C S	0.00	-0.01	0.04^c	6.61	0.03	0.00	0.00	3.06	-0.01	0.02	-0.01	-4.53
		UK Bonds				Int. Bonds				CA		
	Con	$sMkt$	$sLiq$	R^2	Con	$sMkt$	$sLiq$	R^2	Con	$sMkt$	$sLiq$	R^2
L/S LA	0.01	-0.14^a	-0.03	36.21	-0.06	-0.15^a	0.18^a	61.18	0.17^b	-1.12^b	0.03	10.74
L/S C	-0.11^c	0.28^a	-0.00	39.76	0.20^c	-0.10^b	-0.09^b	17.25	-0.03	0.67	-0.15^c	22.70
LA/C L	0.10^c	-0.25^a	-0.02	44.98	-0.11	-0.01	0.06	13.56	0.05	-0.54	0.03	7.09
LA/C S	-0.03	0.16^a	0.01	54.21	0.15	0.05	-0.21^b	23.39	-0.15^c	1.25^a	-0.15^a	33.44

The table reports regressions of the post-ranking spread portfolio returns of asset j on the relevant (external benchmark) market return for asset class j and liquidity effects. The month t cross-section of pension fund returns is double sorted by the size of the fund and the sector type. We first sort the funds into terciles by asset size (small, medium and large), and then we group the funds in each portfolio according to the sector type of the fund (private and public). We report the results from four spread portfolios regressions. Specifically, we estimate:

$$r_{j,t}^a - r_{j,t}^b = \alpha + \beta_1 Mkt_{j,t} + \beta_2 Mkt_{j,t-1} + \gamma_1 Liq_t + \gamma_2 Liq_{t-1} + \varepsilon_t,$$

where $r_{j,t}^a - r_{j,t}^b$ is the differential in returns between portfolios a and b for asset class j. The four spread portfolios are large minus small for local authorities (L/S LA), large minus small for corporates (L/S C), and large local authorities minus large corporates (LA/C L) and small local authorities minus small corporates (LA/C S). $Mkt_{j,t}$ is the 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). $sMkt$ ($sLiq$) 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 global financial crisis and its aftermath from January 2008 to December 2012 in Panel B. R^2sdenote 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. 'Con' is the constant term in the regression, 'CA' refers to cash/alternatives and 'UK IL' refers to UK index-linked bonds.

II.2 Spread Portfolio Net Investment

In this subsection, we analyze spread portfolio flow effects, to complement the analysis reported in Section 5.1 for flow effects of the peer-group benchmark case. We perform a similar 3×2 portfolio sort to the return regressions of Table A5 to further analyze flow effects by focusing on funds of different size and sector type. Specifically, we estimate:

$$\widetilde{NCF}_{j,t}^{a} - \widetilde{NCF}_{j,t}^{b} = \alpha + \sum_{s=0}^{3} \beta_s Mkt_{t-s} + \sum_{s=0}^{3} \gamma_s Liq_{t-s} + \varepsilon_t, \qquad \text{(II.2)}$$

where, for portfolio a, $\widetilde{NCF}_{j,t}^{a}$ is defined as $ncf_{j,t}^{a} - ncf_{p,t}^{a}$, with $ncf_{j,t}^{a}$ and $ncf_{p,t}^{a}$ denoting the net cash flow rates of the average fund of portfolio a into asset class j and into the total portfolio, respectively, during month t. The dependent variable is therefore the differential change in return-adjusted weights (i.e., net cash flow differentials) of portfolios a and b for asset j. Eq. II.2 allows us to highlight differences in the behavior of private- and public-sector funds, and between funds of different sizes.

Table A6 shows a number of interesting results on the size effect. Over the whole period, Panel A shows that small funds exhibit a bigger market effect ($sMkt$) than large funds in all asset categories, except international bonds. This holds for both private- and public-sector funds. In terms of liquidity shocks ($sLiq$), there are generally no significant differential responses, except in the case of UK equities and UK bonds. For UK equities, small public-sector funds display a bigger response than large public-sector funds. For UK bonds, large funds increase their return-adjusted weight more than small funds as liquidity improves and market prices fall. In other words, large funds are more procyclical and perform more portfolio rebalancing than small funds in their allocations to domestic bonds. There are no significant differences between private- and public-sector funds in terms of their reaction to liquidity shocks, except marginally in the case of UK index-linked bonds and cash/alternatives. Analysis of the constant term reveals that large private-sector funds de-risked more than either large public-sector funds or small private-sector funds by making larger switches from equities to bonds, which is consistent with large corporate funds being more mature than either large local authority funds, which are still open to new members, or small corporate funds. Large private-sector funds also invested more in alternative assets such as hedge funds than either large public-sector funds or small private-sector funds. In contrast, there are no substantial differences in the strategic asset re-allocations between public-sector funds of different sizes, which could reflect the nature of the sponsor.

Panel B shows that the market and liquidity effect results were broadly unchanged during the crisis period. The exception is UK bonds: there is no longer a differential market effect between large and small funds, but the differential liquidity effect between large and small funds strengthens considerably. This is clearly a consequence of quantitative easing in the UK. However, the constant terms reveal some changes in the funds' differential longer-term strategic asset allocations during the crisis period. The most notable change is that private-sector funds accelerated their disinvestment in UK equities relative to public-sector funds. Small private-sector funds also decreased their weighting in international bonds relative to either large private-sector funds or other small public-sector funds.

Overall, the key finding in this section is that large private-sector funds de-risked the most over the period and this accelerated during the recent crisis.

Table A6: **Regressions of Spread Portfolio Net Cash Flows on Asset Market Returns and Liquidity**

| | Panel A: 1995-2012 | | | | | | | | | | | |
| | UK Equities | | | | Int. Equities | | | | UK IL | | | |
	Con	$sMkt$	$sLiq$	R^2	Con	$sMkt$	$sLiq$	R^2	Con	$sMkt$	$sLiq$	R^2
L/S LA	0.02	−0.02	−0.09^b	14.30	−0.01	−0.03	−0.10	2.83	0.17	−0.12	0.13	−0.48
L/S C	−0.10^a	−0.02	0.02	1.34	−0.07^b	−0.05^a	0.01	11.58	0.42^a	0.04	−0.17	−1.14
LA/C L	0.16^a	0.02	−0.08	2.60	0.03	0.03	−0.06	4.72	−0.50^a	−0.01	−0.00	−1.88
LA/C S	0.04	0.02	0.03	10.27	−0.04	0.00	0.04	0.05	−0.25	0.14	−0.30^c	2.25
	UK Bonds				Int. Bonds				CA			
	Con	$sMkt$	$sLiq$	R^2	Con	$sMkt$	$sLiq$	R^2	Con	$sMkt$	$sLiq$	R^2
L/S LA	0.07	−0.51^a	0.28^b	4.91	0.16	0.62^b	0.09	−0.66	−0.70	−1.80	0.55	−1.79
L/S C	0.15^c	−0.22^b	0.18^b	1.23	0.60	0.61^c	−0.35	3.72	1.37^c	−5.57^a	0.14	2.33
LA/C L	−0.08	−0.03	0.01	−1.07	0.61	0.06	0.16	−1.45	−1.64^b	2.41	0.99^b	−1.49
LA/C S	0.00	0.26	−0.10	−2.43	1.06^a	0.05	−0.27	2.84	0.42	−1.36	0.58	−0.90
	Panel B: 2008-2012											
	UK Equities				Int. Equities				UK IL			
	Con	$sMkt$	$sLiq$	R^2	Con	$sMkt$	$sLiq$	R^2	Con	$sMkt$	$sLiq$	R^2
L/S LA	−0.11	0.02	−0.14^b	16.85	−0.03	−0.03	0.04	−1.97	−0.03	−0.19	0.00	−5.95
L/S C	−0.06	0.03	−0.06	−3.92	−0.14^a	−0.07^b	0.07	25.83	0.43^b	−0.05	−0.22^c	−2.86
LA/C L	0.26^a	0.08	−0.16	−3.01	0.01	0.06	−0.08	3.27	−0.44^b	−0.13	0.13	−6.80
LA/C S	0.31^a	0.09^b	−0.08	17.45	−0.10^c	0.02	−0.05	−7.79	0.02	0.01	−0.09	1.75
	UK Bonds				Int. Bonds				CA			
	Con	$sMkt$	$sLiq$	R^2	Con	$sMkt$	$sLiq$	R^2	Con	$sMkt$	$sLiq$	R^2
L/S LA	−0.11	−0.04	0.34^a	24.58	0.70	0.96^b	0.10	−3.13	−0.36	−5.20	0.18	−6.85
L/S C	−0.07	−0.20	0.27^a	13.28	3.22^a	0.59	−0.72	20.65	1.35^b	−7.20^c	−0.73	1.27
LA/C L	0.01	0.05	−0.06	4.74	0.87	−0.14	0.05	−5.50	−1.26^c	0.06	1.23^c	10.09
LA/C S	0.05	−0.12	−0.13^c	7.57	3.38^a	−0.51	−0.76	2.40	0.46	−1.94	0.32	−4.93

The table reports the post-ranking portfolios' net cash flow differential regressions on asset market returns and liquidity effects. The month t cross-section of pension fund net cash flow differentials, $\widetilde{NCF}_{j,t}$, are double sorted by the size of the fund and by the sector type. We first sort the funds into terciles by asset size (small, medium and large), and then we group the funds in each portfolio according to the sector type of the fund (private and public). We report the results from four spread portfolios regressions. Specifically, we estimate:

$$\widetilde{NCF}_{j,t}^{a} - \widetilde{NCF}_{j,t}^{b} = \alpha + \sum_{s=0}^{3} \beta_s Mkt_{j,t-s} + \sum_{s=0}^{3} \gamma_s Liq_{t-s} + \varepsilon_t,$$

where $\widetilde{NCF}_{j,t}^{a} - \widetilde{NCF}_{j,t}^{b}$ is the net cash flow differential between portfolios a and b for asset class j. The four spread portfolios are large minus small for local authorities (L/S LA), large minus small for corporates (L/S C), and large local authorities minus large corporates (LA/C L) and small local authorities minus small corporates (LA/C S). $Mkt_{j,t}$ is the 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). $sMkt$ ($sLiq$) denotes the sum of contemporaneous and lagged betas (gammas) with the relative t-statistics. 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-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. 'Con' is the constant term in the regression, 'CA' refers to cash/alternatives and 'UK IL' refers to UK index-linked bonds.

Table A7: **Regressions of Portfolio Returns on Asset Market Returns and Liquidity, Decomposed by Sector Type and Fund Size: 1995-2012**

	Con	Mkt_t	Mkt_{t-1}	Liq_t	Liq_{t-1}	$sMkt$	$sLiq$	R^2
				UK Equities				
SC	0.12^a	0.97^a	0.01	-0.01	-0.00	0.98^a	-0.02	99.67
SLA	0.10^a	0.98^a	-0.00	0.00	0.01	0.98^a	0.01	99.61
MC	0.13^a	0.97^a	0.00	-0.02	0.00	0.98^a	-0.02	99.63
MLA	0.10^a	0.98^a	0.00	-0.01	0.01	0.99^a	0.00	99.61
LC	0.10^a	0.98^a	0.00	-0.02	0.00	0.98^a	-0.02	99.76
LLA	0.10^a	0.98^a	0.00	-0.00	0.01	0.98^a	0.01	99.63
L/S LA	0.00	0.00	0.00	-0.01	0.00	0.01	-0.00	-0.22
L/S C	-0.01	0.01^b	-0.00	-0.01	0.01	0.00	-0.00	1.48
LA/C L	-0.00	0.00	-0.00	0.02^b	0.01	0.00	0.03^a	4.02
LA/C S	-0.01	0.00	-0.01^c	0.02	0.01	-0.00	0.03	5.39
				International Equities				
SC	0.09	0.95^a	0.04^b	0.18^a	0.01	0.99^a	0.19^a	96.02
SLA	0.09	0.96^a	0.04^c	0.17^a	0.03	1.00^a	0.20^a	95.09
MC	0.12^b	0.97^a	0.03^b	0.11^a	0.02	1.00^a	0.13^a	96.94
MLA	0.09	0.96^a	0.04^c	0.14^a	0.02	1.00^a	0.16^a	95.85
LC	0.09	0.97^a	0.03^c	0.10^b	0.01	1.00^a	0.10^b	96.99
LLA	0.12^c	0.95^a	0.04^b	0.19^a	0.02	0.99^a	0.20^a	95.66
L/S LA	0.02	-0.01^a	0.00	0.01	-0.01	-0.01	0.00	1.74
L/S C	-0.00	0.02^a	-0.01	-0.08^a	-0.01	0.01^c	-0.09^a	11.32
LA/C L	0.02	-0.03^a	0.01^b	0.09^a	0.01	-0.01^b	0.10^a	17.68
LA/C S	0.00	0.01	0.00	-0.00	0.01	0.01	0.01	-0.59
				UK Bonds				
SC	-0.01	1.06^a	0.03	0.06^a	0.05^a	1.09^a	0.12^a	95.87
SLA	-0.04	1.13^a	0.02	0.07^a	0.06^a	1.15^a	0.13^a	94.84
MC	-0.04	1.13^a	0.02	0.05^a	0.03	1.14^a	0.08^a	96.41
MLA	-0.02	1.07^a	0.03	0.06^a	0.06^a	1.11^a	0.12^a	95.43
LC	-0.05^c	1.13^a	0.05^b	0.06^a	0.07^a	1.18^a	0.14^a	96.72
LLA	-0.00	1.04^a	0.03^c	0.05^a	0.05^a	1.07^a	0.10^a	96.57
L/S LA	0.04^b	-0.09^a	0.01	-0.02	-0.02	-0.08^a	-0.04^c	30.93
L/S C	-0.04	0.07^a	0.02	0.00	0.02	0.09^a	0.02	10.67
LA/C L	0.04^b	-0.10^a	-0.02	-0.01	-0.03^b	-0.11^a	-0.04^b	24.43
LA/C S	-0.03^b	0.07^a	-0.01	0.01	0.01	0.06^a	0.02	19.46

	Con	Mkt_t	Mkt_{t-1}	Liq_t	Liq_{t-1}	$sMkt$	$sLiq$	R^2
				International Bonds				
SC	0.16^a	0.75^a	0.05^c	0.42^a	0.15^a	0.79^a	0.57^a	83.01
SLA	0.16^a	0.81^a	0.02	0.30^a	0.08^b	0.83^a	0.37^a	91.09
MC	0.28^a	0.65^a	0.04	0.47^a	0.15^b	0.70^a	0.62^a	70.32
MLA	0.23^a	0.67^a	0.04	0.41^a	0.24^a	0.71^a	0.65^a	76.90
LC	0.28^a	0.78^a	-0.02	0.34^a	0.16^b	0.75^a	0.50^a	84.18
LLA	0.20^a	0.70^a	0.01	0.30^a	0.23^a	0.71^a	0.52^a	86.16
L/S LA	0.04	-0.11^a	-0.01	-0.00	0.15^a	-0.12^a	0.15^b	45.81
L/S C	0.12^a	0.03	-0.07^a	-0.08^b	0.01	-0.04	-0.07^c	11.42
LA/C L	-0.08^b	-0.08^a	0.04^b	-0.04	0.07^b	-0.04	0.02	16.01
LA/C S	0.00	0.07^a	-0.03	-0.12^c	-0.08^b	0.04	-0.20^b	17.54
	Con	Mkt_t	Mkt_{t-1}	Liq_t	Liq_{t-1}	$sMkt$	$sLiq$	R^2
				UK IL				
SC	0.01	1.06^a	-0.01^a	0.04^a	0.01^c	1.04^a	0.05^a	99.55
SLA	0.01	1.06^a	-0.01^c	0.04^a	0.00	1.05^a	0.04^a	99.17
MC	-0.02	1.12^a	-0.02^b	0.05^a	-0.02	1.10^a	0.02	99.00
MLA	0.01	1.06^a	-0.01	0.01	-0.01^c	1.05^a	-0.01	99.56
LC	0.01	1.06^a	-0.01	0.01	-0.02^b	1.05^a	-0.01	99.49
LLA	0.02^b	1.04^a	-0.01^c	0.02^b	-0.02^c	1.03^a	0.00	99.66
L/S LA	0.01	-0.02^b	0.00	-0.02^b	-0.02^b	-0.02^b	-0.04^a	16.42
L/S C	0.01	0.01	0.01	-0.02^c	-0.04^a	0.01	-0.06^a	16.75
LA/C L	0.01	-0.02^a	0.00	0.01	0.01	-0.02^a	0.01	7.12
LA/C S	0.00	0.01	0.00	0.00	-0.01	0.01	-0.01	-0.65
	Con	Mkt_t	Mkt_{t-1}	Liq_t	Liq_{t-1}	$sMkt$	$sLiq$	R^2
				CA				
SC	0.12	0.46	0.24	0.16^a	0.03	0.70^a	0.19^a	31.32
SLA	0.04	0.38	0.50	0.07^a	-0.02	0.88^a	0.05^b	32.08
MC	0.09	1.03	-0.31	0.10^a	-0.00	0.72^a	0.10^b	16.04
MLA	0.10	1.19^b	-0.48	0.17^a	0.01	0.71^a	0.18^a	34.47
LC	0.12	0.19	0.65	0.10^b	-0.05	0.83^a	0.05	12.58
LLA	0.11	1.32^c	-0.53	0.10^b	-0.01	0.79^a	0.09	18.66
L/S LA	0.07	0.94	-1.02	0.03	0.02	-0.08	0.04	1.27
L/S C	0.00	-0.27	0.41	-0.06^b	-0.08^a	0.13	-0.14^a	11.09
LA/C L	-0.01	1.13^b	-1.17^a	-0.00	0.04^b	-0.04	0.04^c	3.78
LA/C S	-0.07	-0.08	0.26	-0.09^b	-0.05^a	0.17	-0.14^a	17.19

11

	Property							
	Con	Mkt_t	Mkt_{t-1}	Liq_t	Liq_{t-1}	$sMkt$	$sLiq$	R^2
SC	0.02	0.96^a	-0.03	-0.05	-0.05	0.94^a	-0.09^a	86.13
SLA	-0.01	0.77^a	0.17^c	0.02	-0.07^b	0.95^a	-0.05	84.80
MC	0.12^a	0.87^a	0.01	-0.03	-0.06	0.88^a	-0.09^b	82.21
MLA	-0.08^c	0.95^a	0.08	0.02	-0.10^b	1.04^a	-0.08	88.45
LC	0.01	1.27^a	-0.25^c	-0.11^c	-0.13	1.02^a	-0.24^b	68.65
LLA	0.04	0.86^a	0.05	-0.01	-0.08	0.91^a	-0.09	81.89
L/S LA	0.05	0.08	-0.12	-0.04	-0.01	-0.03	-0.04	0.45
L/S C	-0.00	0.31^c	-0.22^b	-0.06	-0.09	0.09	-0.15	6.52
LA/C L	0.02	-0.42^a	0.30^a	0.10^b	0.06	-0.11	0.15^b	12.10
LA/C S	-0.02	-0.19^c	0.20^c	0.07^b	-0.02	0.01	0.05	7.61

The table reports regressions of the post-ranking portfolio returns of asset j on the relevant (external benchmark) market return for asset class j and liquidity effects. The month t cross-section of pension fund returns are double sorted by the size of the fund and by the sector type. We first sort the funds into terciles by asset size (small, medium and large), and then we group the funds in each portfolio according to the sector type of the fund (private and public). Specifically, we estimate

$$r_{j,t,p} = \alpha + \beta_1 Mkt_{j,t} + \beta_2 Mkt_{j,t-1} + \gamma_1 Liq_t + \gamma_2 Liq_{t-1} + \varepsilon_t$$

where $r_{t,j,p}$ is the post-ranking portfolio return of asset j. We therefore estimate 6 portfolio regressions: SC, MC, and LC denote respectively the small, medium and large corporate pension fund portfolios, and similarly SLA, MLA, and LLA denote the small, medium and large local authority pension fund portfolios. We also estimate four spread portfolios regressions. The four spread portfolios are large minus small for local authorities (L/S LA), large minus small for corporates (L/S C), and large local authorities minus large corporates (LA/C L) and small local authorities minus small corporates (LA/C S). $Mkt_{j,t}$ is the return on the relevant benchmark market 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). $sMkt$ ($sLiq$) denotes the sum of contemporaneous and lagged betas (gammas) with the associated t-statistics beneath. The regression is at a monthly frequency for the 1995-2012 period. 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. 'Con' is the constant term in the regression, 'CA' refers to cash/alternatives and 'UK IL' refers to UK index-linked bonds.

Table A8: **Regressions of Portfolio Returns on Asset Market Returns and Liquidity, Decomposed by Sector Type and Fund Size: 2008-2012**

	Con	Mkt_t	Mkt_{t-1}	Liq_t	Liq_{t-1}	$sMkt$	$sLiq$	R^2
			UK Equities					
SC	0.17^a	0.97^a	0.00	-0.02	-0.00	0.97^a	-0.03	99.79
SLA	0.17^a	0.97^a	-0.01	-0.01	0.02	0.97^a	0.01	99.75
MC	0.19^a	0.96^a	-0.00	-0.03	0.02	0.96^a	-0.01	99.69
MLA	0.15^a	0.99^a	-0.00	-0.03	0.02	0.98^a	-0.01	99.77
LC	0.16^a	0.97^a	0.00	-0.02	0.00	0.97^a	-0.02	99.80
LLA	0.18^a	0.99^a	-0.01	-0.03	0.02	0.99^a	-0.01	99.75
L/S LA	0.01	0.02^a	0.00	-0.02^c	-0.00	0.02^a	-0.03^c	13.93
L/S C	-0.01	0.00	0.00	0.00	0.01	0.00	0.01	-5.22
LA/C L	0.02	0.03^a	-0.01^b	-0.01	0.02	0.01^b	0.00	33.73
LA/C S	0.00	0.01	-0.01	0.01	0.03	-0.01	0.04^c	6.61
			International Equities					
	Con	Mkt_t	Mkt_{t-1}	Liq_t	Liq_{t-1}	$sMkt$	$sLiq$	R^2
SC	0.05	0.94^a	0.02	0.24^a	-0.01	0.97^a	0.22^a	97.99
SLA	0.08	0.97^a	0.00	0.20^a	0.03	0.97^a	0.23^a	98.78
MC	0.07	0.95^a	0.02	0.16^a	0.00	0.97^a	0.16^a	98.89
MLA	0.06	0.97^a	0.02	0.18^a	-0.02	0.99^a	0.16^a	98.95
LC	0.05	0.97^a	0.02	0.14^a	-0.03	0.99^a	0.12^a	99.03
LLA	0.08	0.96^a	0.02	0.21^a	0.01	0.98^a	0.22^a	98.59
L/S LA	-0.00	-0.01	0.01^a	0.02	-0.02^b	0.01	-0.01	4.40
L/S C	-0.00	0.02^b	-0.00	-0.09^a	-0.01	0.02^b	-0.10^a	13.02
LA/C L	0.03	-0.01	-0.00	0.07^a	0.03^c	-0.01	0.10^a	28.76
LA/C S	0.03	0.02^b	-0.02	-0.04	0.05^c	0.00	0.00	3.06
			UK Bonds					
	Con	Mkt_t	Mkt_{t-1}	Liq_t	Liq_{t-1}	$sMkt$	$sLiq$	R^2
SC	0.08	0.97^a	-0.01	0.11^a	0.07^a	0.96^a	0.18^a	93.16
SLA	0.06	1.13^a	-0.00	0.09^b	0.10^a	1.12^a	0.19^a	91.38
MC	0.00	1.13^a	-0.02	0.06^c	0.05^c	1.12^a	0.11^b	93.82
MLA	0.07	0.97^a	0.00	0.11^a	0.08^a	0.98^a	0.19^a	92.09
BC	-0.03	1.20^a	0.04	0.05^c	0.13^a	1.24^a	0.18^a	95.18
BLA	0.07	0.99^a	-0.00	0.09^a	0.07^a	0.99^a	0.16^a	95.15
L/S LA	0.01	-0.14^a	0.00	-0.01	-0.02	-0.14^a	-0.03	36.21
L/S C	-0.11^c	0.23^a	0.05	-0.06^b	0.06^a	0.28^a	-0.00	39.76
LA/C L	0.10^c	-0.21^a	-0.04	0.03	-0.05^a	-0.25^a	-0.02	44.98
LA/C S	-0.03	0.16^a	0.01	-0.02	0.02	0.16^a	0.01	54.21

	Con	Mkt_t	Mkt_{t-1}	Liq_t	Liq_{t-1}	$sMkt$	$sLiq$	R^2
			International Bonds					
SC	0.15	0.63^a	0.09^b	0.52^a	0.08	0.72^a	0.60^a	81.50
SLA	0.30^a	0.73^a	0.03	0.37^a	0.03	0.77^a	0.40^a	90.61
MC	0.33^b	0.47^a	0.08	0.58^a	0.07	0.55^a	0.64^a	71.30
MLA	0.41^a	0.51^a	0.08	0.50^a	0.22^a	0.58^a	0.72^a	71.79
LC	0.35^a	0.65^a	-0.03	0.42^a	0.09	0.62^a	0.51^a	86.07
LLA	0.24^a	0.61^a	0.01	0.35^a	0.23^a	0.61^a	0.57^a	89.37
L/S LA	-0.06	-0.13^a	-0.03	-0.02	0.20^a	-0.15^a	0.18^a	61.18
L/S C	0.20^c	0.02	-0.12^a	-0.11^b	0.01	-0.10^b	-0.09^b	17.25
LA/C L	-0.11	-0.05	0.03	-0.07	0.14^a	-0.01	0.06	13.56
LA/C S	0.15	0.11^b	-0.06^c	-0.16^c	-0.05	0.05	-0.21^b	23.39
	Con	Mkt_t	Mkt_{t-1}	Liq_t	Liq_{t-1}	$sMkt$	$sLiq$	R^2
			UK IL					
SC	0.03^c	1.08^a	-0.01	0.04^a	-0.00	1.07^a	0.04^b	99.66
SLA	0.02	1.09^a	-0.00	0.05^a	-0.02^c	1.09^a	0.03^b	99.31
MC	-0.01	1.17^a	-0.02^c	0.06^a	-0.08^a	1.16^a	-0.02	99.35
MLA	0.03^c	1.09^a	0.00	-0.00	-0.04^a	1.09^a	-0.04^a	99.73
LC	0.05^b	1.09^a	-0.00	0.01	-0.06^a	1.09^a	-0.05^a	99.50
LLA	0.04^b	1.05^a	-0.00	0.02^a	-0.03^a	1.05^a	-0.01	99.73
L/S LA	0.02	-0.04^b	0.00	-0.02^c	-0.01	-0.04^b	-0.04^b	24.26
L/S C	0.02	0.01	0.01	-0.03^c	-0.05^a	0.02	-0.08^a	24.31
LA/C L	-0.01	-0.04^a	-0.00	0.01	0.02	-0.04^b	0.03^c	9.81
LA/C S	-0.01	0.01	0.01	0.01	-0.02^c	0.02	-0.01	-4.53
	Con	Mkt_t	Mkt_{t-1}	Liq_t	Liq_{t-1}	$sMkt$	$sLiq$	R^2
			CA					
SC	0.18^b	3.47^c	-3.53^c	0.22^a	-0.01	-0.07	0.21^a	37.17
SLA	0.03	3.83^c	-2.64	0.12^a	-0.05^c	1.19^a	0.06^c	18.72
MC	0.17^b	4.11	-4.30	0.14^b	-0.05	-0.18	0.09^c	8.70
MLA	0.17^c	5.42^c	-5.52^c	0.24^a	-0.04	-0.10	0.20^a	42.88
LC	0.15	3.82	-3.21	0.12^c	-0.06	0.61	0.07	0.33
LLA	0.20^b	7.20^a	-7.14^a	0.16^a	-0.06	0.07	0.09	14.55
L/S LA	0.17^b	3.37^c	-4.49^b	0.04	-0.01	-1.12^b	0.03	10.74
L/S C	-0.03	0.35	0.33	-0.10	-0.05	0.67	-0.15^c	22.70
LA/C L	0.05	3.39^c	-3.93^b	0.03	-0.01	-0.54	0.03	7.09
LA/C S	-0.15^c	0.36	0.89	-0.11^b	-0.04	1.25^a	-0.15^a	33.44

| | Property | | | | | | | |
	Con	Mkt_t	Mkt_{t-1}	Liq_t	Liq_{t-1}	$sMkt$	$sLiq$	R^2
SC	-0.17^a	0.94^a	-0.11	0.00	-0.08	0.84^a	-0.08	90.25
SLA	-0.26^a	0.68^a	0.20	0.06	-0.08^a	0.88^a	-0.02	87.93
MC	0.00	0.91^a	-0.07	0.00	-0.12^b	0.83^a	-0.11^b	91.61
MLA	-0.24^a	1.09^a	-0.06	0.07^b	-0.19^a	1.03^a	-0.11^b	90.55
LC	0.02	1.64^a	-0.57^a	-0.05	-0.31^b	1.07^a	-0.37^b	74.83
LLA	-0.06	1.04^a	-0.12	0.03	-0.17^a	0.92^a	-0.14^c	84.95
L/S LA	0.20^a	0.36	-0.32	-0.03	-0.09	0.04	-0.12	7.61
L/S C	0.19^b	0.70^a	-0.47^a	-0.06	-0.23^a	0.23^b	-0.29^a	27.58
LA/C L	-0.07	-0.60^a	0.46^a	0.08^b	0.14^b	-0.15	0.23^b	23.90
LA/C S	-0.08	-0.27	0.31^c	0.05	0.00	0.04	0.06	12.65

The table reports regressions of the post-ranking portfolio returns of asset j on the relevant (external benchmark) market return for asset class j and liquidity effects. The month t cross-section of pension fund returns are double sorted by the size of the fund and by the sector type. We first sort the funds into terciles by asset size (small, medium and large), and then we group the funds in each portfolio according to the sector type of the fund (private and public). Specifically, we estimate

$$r_{j,t,p} = \alpha + \beta_1 Mkt_{j,t} + \beta_2 Mkt_{j,t-1} + \gamma_1 Liq_t + \gamma_2 Liq_{t-1} + \varepsilon_t$$

where $r_{t,j,p}$ is the post-ranking portfolio return of asset j. We therefore estimate 6 portfolio regressions: SC, MC, and LC denote respectively the small, medium and large corporate pension fund portfolios, and similarly SLA, MLA, and LLA denote the small, medium and large local authority pension fund portfolios. We also estimate four spread portfolios regressions. The four spread portfolios are large minus small for local authorities (L/S LA), large minus small for corporates (L/S C), and large local authorities minus large corporates (LA/C L) and small local authorities minus small corporates (LA/C S). $Mkt_{j,t}$ is the return on the relevant benchmark market 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). $sMkt$ ($sLiq$) denotes the sum of contemporaneous and lagged betas (gammas) with the associated t-statistics beneath. The regression is at a monthly frequency for the 2008-2012 period. $R^2 s$ 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. 'Con' is the constant term in the regression, 'CA' refers to cash/alternatives and 'UK IL' refers to UK index-linked bonds.

Table A9: **Regressions of Net Cash Flows on Asset Market Returns and Liquidity: 1995-2012**

						UK Equities						
	Con	Mkt_t	Mkt_{t-1}	Mkt_{t-2}	Mkt_{t-3}	Liq_t	Liq_{t-1}	Liq_{t-2}	Liq_{t-3}	$sMkt$	$sLiq$	R^2
SC	-0.29^a	-0.03^a	-0.03^a	-0.02	-0.02^c	-0.01	-0.01	0.01	0.02	-0.10^a	0.01	10.56
SLA	-0.25^a	-0.02^a	0.00	-0.04^a	-0.01	0.04	-0.01	0.04	-0.03	-0.08^a	0.04	9.88
MC	-0.21^a	-0.03^a	-0.03^b	-0.02	-0.03^b	0.03	-0.01	-0.01	0.05	-0.11^a	0.06	11.14
MLA	-0.21^a	-0.04^a	-0.03^b	-0.01	-0.01	-0.02	0.02	-0.01	0.00	-0.08^a	-0.00	18.08
LC	-0.39^a	-0.03^a	-0.04^a	-0.01	-0.04^a	-0.04	-0.01	-0.02	0.11^b	-0.12^a	0.04	12.40
LLA	-0.23^a	-0.04^a	-0.02^c	-0.01	-0.02^b	-0.01	-0.02	-0.04^c	0.03	-0.10^a	-0.04	22.70
L/S LA	0.02	-0.02^b	-0.02^a	0.03^a	-0.00	-0.05^b	-0.01	-0.08^a	0.06	-0.02	-0.09^b	14.30
L/S C	-0.10^a	-0.01	-0.01	0.01	-0.02^c	-0.03	-0.00	-0.03	0.09^a	-0.02	0.02	1.34
LA/C L	0.16^a	-0.01	0.02^c	-0.01	0.02^b	0.03	-0.00	-0.02	-0.08^b	0.02	-0.08	2.60
LA/C S	0.04	0.00	0.04^a	-0.03^a	0.01	0.05^c	0.00	0.03	-0.05	0.02	0.03	10.27
						International Equities						
	Con	Mkt_t	Mkt_{t-1}	Mkt_{t-2}	Mkt_{t-3}	Liq_t	Liq_{t-1}	Liq_{t-2}	Liq_{t-3}	$sMkt$	$sLiq$	R^2
SC	0.16^a	0.00	-0.02	-0.02^a	-0.02^c	0.01	0.01	0.04	0.05^c	-0.05^b	0.12	1.40
SLA	0.13	-0.02	0.00	-0.03	-0.01	0.07	-0.03	0.09^b	0.03	-0.05	0.16	-0.67
MC	0.06	-0.02^c	-0.01	-0.01	-0.02^b	0.02	-0.06	0.02	0.05^c	-0.06^b	0.03	3.83
MLA	0.07	-0.03^b	-0.04^a	-0.02	-0.03^b	0.03	0.04	0.06^c	0.08^a	-0.11^a	0.21^b	8.23
LC	0.09^c	-0.00	-0.05^a	-0.02^a	-0.03^a	-0.01	-0.02	0.10^a	0.06^b	-0.11^a	0.13^c	18.26
LLA	0.12^b	-0.01	-0.02^c	-0.02^c	-0.03^a	-0.01	-0.00	0.01	0.07^a	-0.08^a	0.06	6.15
L/S LA	-0.01	0.01	-0.03^c	0.01	-0.02^c	-0.08^b	0.02	-0.07^b	0.04	-0.03	-0.10	2.83
L/S C	-0.07^b	-0.00	-0.03^a	-0.00	-0.02^b	-0.02	-0.04	0.06^c	0.01	-0.05^a	0.01	11.58
LA/C L	0.03	-0.01	0.02^a	0.00	0.00	-0.00	0.02	-0.09^a	0.01	0.03	-0.06	4.72
LA/C S	-0.04	-0.02^c	0.02^c	-0.00	0.01	0.06^b	-0.04	0.04	-0.02	0.00	0.04	0.05
						UK Bonds						
	Con	Mkt_t	Mkt_{t-1}	Mkt_{t-2}	Mkt_{t-3}	Liq_t	Liq_{t-1}	Liq_{t-2}	Liq_{t-3}	$sMkt$	$sLiq$	R^2
SC	0.76^a	-0.08	-0.07	-0.10	0.08	-0.02	0.06	0.09^c	-0.13^c	-0.16	-0.00	0.59
SLA	0.76^a	0.06	-0.04	-0.12	0.20	-0.16	0.13	0.12	-0.19^c	0.11	-0.10	-1.61
MC	0.63^a	-0.10	0.06	0.01	0.04	-0.02	-0.03	0.25^a	-0.19^b	0.00	0.01	2.24
MLA	0.83^a	-0.08	0.01	-0.14	0.18	-0.09	0.15	0.30^c	-0.22	-0.02	0.13	-0.92
LC	0.91^a	-0.18^a	-0.14^b	-0.11^c	0.07	-0.01	0.18^a	0.06	-0.05	-0.37^b	0.18	6.05
LLA	0.84^a	-0.15	-0.20^c	-0.17^c	0.11	-0.02	0.13	0.32^a	-0.24^b	-0.40^c	0.18	2.12
L/S LA	0.07	-0.20^b	-0.16^b	-0.05	-0.09	0.14^c	-0.01	0.20^a	-0.05	-0.51^a	0.28^b	4.91
L/S C	0.15^c	-0.10^c	-0.08	-0.02	-0.02	0.02	0.12^b	-0.04	0.08^c	-0.22^b	0.18^b	1.23
LA/C L	-0.08	0.03	-0.05	-0.05	0.05	-0.02	-0.05	0.27^a	-0.19^b	-0.03	0.01	-1.07
LA/C S	0.00	0.14	0.03	-0.02	0.12	-0.14^c	0.07	0.03	-0.06	0.26	-0.10	-2.43

					International Bonds						
	Con	Mkt_t	Mkt_{t-1}	Mkt_{t-2}	Mkt_{t-3}	Liq_t	Liq_{t-1}	Liq_{t-2}	Liq_{t-3}	$sMkt$	$sLiq$	R^2
SC	-0.95^c	-0.58^a	-0.52^a	0.05	-0.15	0.47	-0.48	-0.53^c	0.70^c	-1.20^a	0.16	11.51
SLA	0.11	-0.45^a	-0.40^b	-0.15	-0.15	-0.09	0.11	-0.37	0.24	-1.15^a	-0.11	3.82
MC	-0.62	-0.48^b	0.02	0.10	0.08	0.37	0.22	-0.58	0.78^c	-0.28	0.79	0.86
MLA	-0.18	-0.51^a	-0.36^c	0.20	-0.19	0.06	0.00	-0.75^a	0.15	-0.86^a	-0.54	4.59
LC	-0.34	-0.50^a	-0.13	-0.02	0.06	0.22	-0.15	-0.58	0.31	-0.59^c	-0.19	2.32
LLA	0.27	-0.27^a	-0.22^c	0.05	-0.08	0.13	-0.01	-0.24	0.09	-0.53^a	-0.03	2.67
L/S LA	0.16	0.18	0.18	0.20	0.07	0.22	-0.12	0.13	-0.15	0.62^b	0.09	-0.66
L/S C	0.60	0.08	0.39^b	-0.07	0.21	-0.25	0.33	-0.05	-0.38	0.61^c	-0.35	3.72
LA/C L	0.61	0.23^c	-0.09	0.06	-0.14	-0.09	0.14	0.34	-0.23	0.06	0.16	-1.45
LA/C S	1.06^a	0.13	0.12	-0.20	0.00	-0.56^b	0.59^b	0.16	-0.46	0.05	-0.27	2.84
					UK IL						
	Con	Mkt_t	Mkt_{t-1}	Mkt_{t-2}	Mkt_{t-3}	Liq_t	Liq_{t-1}	Liq_{t-2}	Liq_{t-3}	$sMkt$	$sLiq$	R^2
SC	0.04	0.04	-0.21^a	-0.01	-0.09^c	0.11	0.13	0.09	-0.02	-0.27^b	0.31^c	4.04
SLA	-0.21	0.17	-0.27^a	0.02	-0.05	0.10	-0.19	0.18	-0.09	-0.13	0.01	2.84
MC	0.14	0.02	-0.13^b	-0.03	-0.05	0.06	0.07	-0.03	0.01	-0.19	0.11	-0.17
MLA	0.00	0.00	-0.31^a	0.02	-0.11	0.22^c	-0.06	0.05	-0.07	-0.40^c	0.14	4.34
LC	0.46^a	0.01	-0.14^a	-0.06	-0.04	0.05	0.01	0.11^b	-0.03	-0.23^b	0.14	1.59
LLA	-0.04	0.03	-0.14^c	-0.04	-0.10	0.12^c	-0.07	0.08	0.01	-0.25	0.14	1.31
L/S LA	0.17	-0.14	0.13	-0.06	-0.05	0.02	0.11	-0.10	0.10	-0.12	0.13	-0.48
L/S C	0.42^a	-0.03	0.07	-0.05	0.05	-0.06	-0.12	0.02	-0.01	0.04	-0.17	-1.14
LA/C L	-0.50^a	0.02	-0.00	0.03	-0.06	0.07	-0.08	-0.03	0.04	-0.01	-0.00	-1.88
LA/C S	-0.25	0.13^c	-0.06	0.04	0.03	-0.01	-0.31^a	0.09	-0.07	0.14	-0.30^c	2.25
					Cash/Alternatives						
	Con	Mkt_t	Mkt_{t-1}	Mkt_{t-2}	Mkt_{t-3}	Liq_t	Liq_{t-1}	Liq_{t-2}	Liq_{t-3}	$sMkt$	$sLiq$	R^2
SC	1.19	25.60^c	5.80	6.78	-32.72^b	-0.18	-0.02	-0.15	0.18	5.46^b	-0.18	4.68
SLA	1.61^c	39.74^c	7.38	-18.57	-24.45	0.71^b	0.06	-0.17	-0.19	4.10	0.40	1.31
MC	1.83^c	31.31^c	-8.18	-0.05	-19.70	0.77^b	-0.34	0.60	-0.44	3.38	0.58	0.47
MLA	1.16^b	16.22	8.75	2.16	-24.09^b	0.16	0.20	-0.04	0.03	3.04^c	0.35	1.93
LC	2.56^a	36.65^b	-19.29	-2.23	-15.24	0.40	0.01	-0.50	0.04	-0.11	-0.04	1.30
LLA	0.91^b	26.93^a	-8.10	-6.04	-10.50	0.68^a	0.08	0.25	-0.07	2.30^c	0.95^a	6.46
L/S LA	-0.70	-12.81	-15.48	12.54	13.95	-0.02	0.02	0.42	0.13	-1.80	0.55	-1.79
L/S C	1.37^c	11.04	-25.08	-9.01	17.48	0.59^c	0.04	-0.35	-0.13	-5.57^a	0.14	2.33
LA/C L	-1.64^b	-9.72	11.19	-3.80	4.74	0.28	0.07	0.75^b	-0.11	2.41	0.99^b	-1.49
LA/C S	0.42	14.14	1.58	-25.35	8.27	0.89^b	0.09	-0.02	-0.37	-1.36	0.58	-0.90

	Property										
	Con	Mkt_t	Mkt_{t-1}	Mkt_{t-2}	Mkt_{t-3}	Liq_t	Liq_{t-1}	Liq_{t-2}	Liq_{t-3}	$sMkt$	$sLiq$	R^2
SC	0.06	-0.04	0.24	-0.04	0.03	0.02	0.04	-0.03	-0.01	0.19^c	0.02	2.48
SLA	0.03	0.04	0.09	-0.09	0.08	0.01	-0.03	0.00	-0.01	0.12^a	-0.03	0.07
MC	0.10	-0.00	0.12	-0.06	0.10	0.01	0.02	-0.00	0.03	0.16	0.06	-0.22
MLA	0.12^c	0.21	0.03	0.09	-0.10	0.03	-0.05	-0.01	-0.02	0.24^a	-0.04	6.56
LC	0.18^a	-0.04	-0.02	0.15	-0.02	0.02	-0.00	0.01	0.05	0.07^c	0.08	0.49
LLA	0.13^b	0.15	0.09	-0.09	0.03	-0.00	-0.02	-0.00	0.00	0.17^a	-0.03	4.05
L/S LA	0.10^b	0.11	0.00	-0.00	-0.05	-0.01	0.01	-0.01	0.01	0.05	0.00	-2.10
L/S C	0.12^b	0.00	-0.26	0.19	-0.05	0.00	-0.04	0.04	0.05	-0.12	0.06	0.88
LA/C L	-0.05	0.19^c	0.11	-0.24^c	0.05	-0.03	-0.02	-0.01	-0.04	0.10^b	-0.10	1.24
LA/C S	-0.03	0.08	-0.15	-0.05	0.05	-0.01	-0.07	0.03	-0.00	-0.07	-0.05	-0.96

The table reports the post-ranking portfolios' net cash flow regressions on market returns and liquidity effects. The month t cross-section of pension fund net cash flow differentials, $\widetilde{NCF}_{j,t} = ncf_{j,t} - ncf_{p,t}$, are double sorted by fund size and sector type. We first sort the funds into terciles by asset size (small, medium and large), and then we group the funds in each portfolio according to the sector type (private and public). Specifically, we estimate:

$$\widetilde{NCF}_{j,p,t} = \alpha_0 + \sum_{s=0}^{3} \beta_s Mkt_{j,t-s} + \sum_{s=0}^{3} \gamma_s Liq_{t-s} + \varepsilon_t,$$

where $\widetilde{NCF}_{t,j,p}$ is the post-formation portfolio p net cash flow differential of asset j. We therefore end up with 6 portfolios: SC, MC, and LC denote respectively the small, medium and large corporate portfolios, and similarly SLA, MLA, and LLA denote the small, medium and large local authorities portfolios. We also report the estimation results from the following four spread portfolios regressions:

$$\widetilde{NCF}_{j,t}^{a} - \widetilde{NCF}_{j,t}^{b} = \alpha + \sum_{s=0}^{3} \beta_s Mkt_{j,t-s} + \sum_{s=0}^{3} \gamma_s Liq_{t-s} + \varepsilon_t,$$

where $\widetilde{NCF}_{j,t}^{a} - \widetilde{NCF}_{j,t}^{b}$ is the net cash flow differential between portfolios a and b for asset class j. The four spread portfolios are large minus small for local authorities (L/S LA), large minus small for corporates (L/S C), and large local authorities minus large corporates (LA/C L) and small local authorities minus small corporates (LA/C S). $Mkt_{j,t}$ is the return on the relevant benchmark market 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). $sMkt$ ($sLiq$) denotes the sum of contemporaneous and lagged betas (gammas). The regression is at monthly frequency for the 1995-2012 period. R^2s denote the adjusted R-squared. 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. 'Con' is the constant term in the regression, 'CA' refers to cash/alternatives and 'UK IL' refers to UK index-linked bonds.

Table A10: **Regressions of Net Cash Flows on Market Returns and Liquidity: 2008-2012**

	Con	Mkt_t	Mkt_{t-1}	Mkt_{t-2}	Mkt_{t-3}	Liq_t	Liq_{t-1}	Liq_{t-2}	Liq_{t-3}	$sMkt$	$sLiq$	R^2
					UK Equities							
SC	-0.54^a	-0.07^a	-0.08^a	-0.04	-0.06^b	0.01	0.07	0.03	0.14^a	-0.25^a	0.24^b	29.01
SLA	-0.23^a	-0.05^a	-0.02	-0.07^a	-0.02	0.06	0.03	0.07^c	0.01	-0.16^a	0.16^c	19.22
MC	-0.35^a	-0.05^b	-0.07^a	-0.04	-0.06^b	0.03	0.05	0.04	0.10^c	-0.23^a	0.22^b	23.17
MLA	-0.22^a	-0.06^a	-0.06^a	-0.02	-0.02	-0.02	0.07	0.01	0.05^c	-0.16^a	0.10	37.26
LC	-0.60^a	-0.05^b	-0.07^a	-0.01	-0.08^a	-0.04	0.04	-0.04	0.23^a	-0.22^a	0.18	21.44
LLA	-0.33^a	-0.05^a	-0.04^a	-0.02	-0.03^c	-0.03	0.01	-0.04	0.08^b	-0.14^a	0.02	41.48
L/S LA	-0.11	0.00	-0.03	0.05^a	-0.00	-0.09^a	-0.02	-0.11^a	0.08	0.02	-0.14^b	16.85
L/S C	-0.06	0.02	0.01	0.03	-0.02	-0.05	-0.03	-0.07	0.09	0.03	-0.06	-3.92
LA/C L	0.26^a	0.01	0.03	-0.01	0.06^b	0.01	-0.03	-0.00	-0.14^b	0.08	-0.16	-3.01
LA/C S	0.31^a	0.02	0.06^a	-0.03	0.04^c	0.05	-0.04	0.04	-0.13^a	0.09^b	-0.08	17.45
					International Equities							
SC	0.13^b	-0.02	-0.02	-0.03^c	0.01	-0.00	-0.01	0.06^b	-0.02	-0.05	0.03	3.13
SLA	0.03	-0.00	-0.02	-0.01	-0.00	0.01	-0.03	0.05	-0.04	-0.03	-0.02	0.69
MC	0.00	-0.01	-0.05^c	-0.01	-0.01	0.01	-0.05	0.03	0.02	-0.08	0.02	14.87
MLA	-0.03	-0.00	-0.02^b	-0.02	0.00	-0.03^b	0.00	0.04^b	0.01	-0.04	0.02	17.45
LC	-0.00	-0.00	-0.09^a	0.01	-0.03	-0.04	0.05	0.04	0.06	-0.12^b	0.10	21.99
LLA	0.01	-0.01	-0.04^a	-0.00	-0.01	-0.02	0.01	-0.02	0.05^b	-0.06^b	0.02	21.64
L/S LA	-0.03	-0.01	-0.01	0.01	-0.01	-0.03	0.04	-0.06	0.09^a	-0.03	0.04	-1.97
L/S C	-0.14^a	0.01	-0.07^a	0.03^a	-0.05^a	-0.04	0.06	-0.02	0.07^b	-0.07^b	0.07	25.83
LA/C L	0.01	-0.00	0.05^b	-0.01	0.02	0.03	-0.04	-0.06	-0.01	0.06	-0.08	3.27
LA/C S	-0.10^c	0.01	0.00	0.02	-0.01	0.01	-0.02	-0.01	-0.02	0.02	-0.05	-7.79
					UK Bonds							
SC	0.20^c	-0.06	-0.08	0.03	-0.03	-0.03	0.07	0.01	-0.07	-0.13	-0.02	0.45
SLA	0.26^c	-0.02	-0.14	-0.09	-0.00	-0.07	0.04	-0.08	-0.05	-0.25	-0.16^c	-3.87
MC	0.12	-0.02	-0.03	0.01	-0.02	-0.01	0.04	0.15^a	-0.12	-0.06	0.06	9.21
MLA	-0.04	-0.07	0.04	-0.05	0.00	-0.02	0.03	0.04	0.01	-0.08	0.06	-6.60
LC	0.14	-0.18^a	-0.06	-0.08	-0.01	-0.01	0.18^a	-0.00	0.08^c	-0.34^b	0.24^a	17.62
LLA	0.15	-0.19^a	-0.15^a	0.03	0.02	0.01	0.09^b	0.09^b	0.00	-0.29^b	0.19^a	32.68
L/S LA	-0.11	-0.17^b	-0.01	0.12^b	0.02	0.08	0.05	0.16^c	0.05	-0.04	0.34^a	24.58
L/S C	-0.07	-0.13^b	0.02	-0.12^b	0.02	0.02	0.11^b	-0.01	0.14^a	-0.20	0.27^a	13.28
LA/C L	0.01	-0.01	-0.08	0.11^b	0.02	0.01	-0.09	0.09	-0.07	0.05	-0.06	4.74
LA/C S	0.05	0.03	-0.06	-0.12^b	0.02	-0.04	-0.02	-0.08	0.02	-0.12	-0.13^c	7.57

	Con	Mkt_t	Mkt_{t-1}	Mkt_{t-2}	Mkt_{t-3}	Liq_t	Liq_{t-1}	Liq_{t-2}	Liq_{t-3}	$sMkt$	$sLiq$	R^2
				International Bonds								
SC	-3.60^a	-0.65^b	-0.57^c	0.61^b	-0.26	0.64^b	-0.40	-0.67^c	1.33^a	-0.87	0.90	24.00
SLA	-0.22	-0.81^a	-0.45	0.14	-0.25	-0.25	0.46	-0.82	0.74	-1.38^b	0.14	3.34
MC	-1.68	-0.45^c	-0.00	0.43	0.04	0.32	0.45	-0.58	1.34^b	0.02	1.53^b	0.39
MLA	-1.82	-0.59^c	-0.28	0.52^c	-0.27	-0.18	0.49	-0.93	0.64	-0.62	0.02	0.63
LC	-0.38	-0.31^b	0.05	0.01	-0.03	0.31	-0.41^c	0.02	0.25	-0.28	0.18	2.87
LLA	0.49	-0.22^c	-0.27^b	0.23^b	-0.16	0.32	-0.23	-0.05	0.20	-0.42^c	0.23	11.56
L/S LA	0.70	0.60^b	0.19	0.09	0.09	0.57	-0.69	0.77	-0.54	0.96^b	0.10	-3.13
L/S C	3.22^a	0.34	0.62^b	-0.60^b	0.23	-0.33	-0.01	0.70^b	-1.08^b	0.59	-0.72	20.65
LA/C L	0.87	0.09	-0.32^c	0.22^c	-0.13	0.01	0.18	-0.08	-0.06	-0.14	0.05	-5.50
LA/C S	3.38^a	-0.17	0.12	-0.47^c	0.01	-0.88^b	0.86^c	-0.14	-0.59	-0.51	-0.76	2.40
	Con	Mkt_t	Mkt_{t-1}	Mkt_{t-2}	Mkt_{t-3}	Liq_t	Liq_{t-1}	Liq_{t-2}	Liq_{t-3}	$sMkt$	$sLiq$	R^2
				UK IL								
SC	-0.34^b	-0.06	-0.06	0.11	0.01	0.15^b	0.22^a	0.00	-0.08	-0.01	0.29^a	10.24
SLA	-0.32^c	0.00	-0.16^b	0.06	0.09	0.14^b	-0.03	0.21^c	-0.13	0.00	0.19	1.12
MC	0.11	-0.01	-0.07	-0.06	-0.02	0.07	0.14^c	0.02	-0.01	-0.17^c	0.23^b	6.83
MLA	-0.26	-0.12	-0.21^b	0.02	-0.04	0.17^c	0.14	0.05	-0.11	-0.35^b	0.26	1.23
LC	0.09	-0.02	-0.05	0.02	-0.00	0.06	0.05	0.05	-0.10	-0.06	0.06	-10.55
LLA	-0.35^c	-0.05	-0.08	0.02	-0.08	0.16^b	0.01	0.06	-0.04	-0.19	0.19	-4.52
L/S LA	-0.03	-0.05	0.08	-0.05	-0.17	0.02	0.04	-0.15	0.09	-0.19	0.00	-5.95
L/S C	0.43^b	0.04	0.01	-0.09	-0.01	-0.09	-0.17^b	0.05	-0.02	-0.05	-0.22^c	-2.86
LA/C L	-0.44^b	-0.03	-0.03	-0.01	-0.07	0.10	-0.04	0.00	0.06	-0.13	0.13	-6.80
LA/C S	0.02	0.06	-0.09	-0.05	0.09	-0.00	-0.25^b	0.21	-0.05	0.01	-0.09	1.75
	Con	Mkt_t	Mkt_{t-1}	Mkt_{t-2}	Mkt_{t-3}	Liq_t	Liq_{t-1}	Liq_{t-2}	Liq_{t-3}	$sMkt$	$sLiq$	R^2
				Cash/Alternatives								
SC	0.73	69.34^b	-22.06	-44.66	5.58	1.19^a	-0.62	-0.12	-0.21	8.21	0.24	6.09
SLA	1.19	27.01	52.32	-130.16^b	57.10	1.18^a	0.13	-0.60	-0.15	6.27	0.56	-0.04
MC	0.85	29.25	56.54	-137.97^a	55.00^a	-0.07	1.22^b	-1.13^a	0.12	2.81	0.15	7.19
MLA	1.12^b	22.95	-9.96	-12.56	2.98	0.24	0.20	-0.11	-0.12	3.41	0.21	-10.22
LC	2.09^a	84.66^a	-20.68	-106.13^a	43.16^a	1.01^a	-0.14	-1.12^a	-0.24	1.01	-0.49	10.52
LLA	0.83^b	-7.07	34.03^b	-34.19^a	8.30	0.55^a	0.21	0.21	-0.23	1.07	0.74^a	22.38
L/S LA	-0.36	-34.08	-18.29	95.97	-48.80	-0.63	0.09	0.81	-0.08	-5.20	0.18	-6.85
L/S C	1.35^b	15.32	1.37	-61.47^c	37.58^b	-0.18	0.48	-1.00^a	-0.03	-7.20^c	-0.73	1.27
LA/C L	-1.26^c	-91.73^a	54.71	71.94^b	-34.86^b	-0.46^c	0.36	1.33^a	0.01	0.06	1.23^c	10.09
LA/C S	0.46	-42.33	74.38	-85.51^c	51.52^c	-0.01	0.75	-0.48	0.06	-1.94	0.32	-4.93

	Con	Mkt_t	Mkt_{t-1}	Mkt_{t-2}	Mkt_{t-3}	Liq_t	Liq_{t-1}	Liq_{t-2}	Liq_{t-3}	$sMkt$	$sLiq$	R^2
					Property							
SC	0.68^a	0.20	0.27	0.00	−0.01	−0.01	0.01	−0.11	−0.07	0.46^a	−0.18	24.79
SLA	0.28^a	0.30^b	−0.15	0.20^b	−0.08	0.01	−0.06	−0.02	−0.06	0.26^a	−0.13	38.18
MC	0.78^a	0.31	0.25	−0.19	0.13	0.01	−0.01	−0.11	−0.03	0.49^a	−0.14	22.28
MLA	0.69^a	0.68^a	−0.16	0.41	$−0.41^b$	0.01	−0.09	$−0.14^b$	−0.10	0.53^a	$−0.32^b$	43.69
LC	0.61^a	0.22^b	−0.14	0.19	−0.04	0.02	−0.04	−0.01	−0.01	0.24^a	−0.04	16.00
LLA	0.65^a	0.33^a	0.11	−0.01	−0.03	−0.02	−0.03	$−0.07^c$	−0.02	0.40^a	$−0.14^c$	46.41
L/S LA	0.36^a	0.03	0.26^c	$−0.21^c$	0.05	−0.02	0.03	$−0.05^c$	0.03	0.14^a	−0.01	6.17
L/S C	−0.07	0.03	−0.41	0.19	−0.03	0.03	−0.05	0.10	0.06	−0.22	0.14	−1.61
LA/C L	0.03	0.11	0.25	−0.20	0.00	−0.04	0.01	−0.06	−0.02	0.16^b	−0.10	−0.89
LA/C S	$−0.40^a$	0.10	−0.42	0.20	−0.07	0.02	−0.07	0.09	0.01	$−0.20^c$	0.05	1.48

The table reports the post-ranking portfolios' net cash flow regressions on market returns and liquidity effects. The month t cross-section of pension fund net cash flow differentials, $\widetilde{NCF}_{j,t} = ncf_{j,t} - ncf_{p,t}$, are double sorted by fund size and sector type. We first sort the funds into terciles by asset size (small, medium and large), and then we group the funds in each portfolio according to the sector type (private and public). Specifically, we estimate:

$$\widetilde{NCF}_{j,p,t} = \alpha_0 + \sum_{s=0}^{3} \beta_s Mkt_{j,t-s} + \sum_{s=0}^{3} \gamma_s Liq_{t-s} + \varepsilon_t,$$

where $\widetilde{NCF}_{t,j,p}$ is the post-formation portfolio p net cash flow differential of asset j. We therefore end up with 6 portfolios: SC, MC, and LC denote respectively the small, medium and large corporate portfolios, and similarly SLA, MLA, and LLA denote the small, medium and large local authorities portfolios. We also report the estimation results from the following four spread portfolios regressions:

$$\widetilde{NCF}_{j,t}^{a} - \widetilde{NCF}_{j,t}^{b} = \alpha + \sum_{s=0}^{3} \beta_s Mkt_{j,t-s} + \sum_{s=0}^{3} \gamma_s Liq_{t-s} + \varepsilon_t,$$

where $\widetilde{NCF}_{j,t}^{a} - \widetilde{NCF}_{j,t}^{b}$ is the net cash flow differential between portfolios a and b for asset class j. The four spread portfolios are large minus small for local authorities (L/S LA), large minus small for corporates (L/S C), and large local authorities minus large corporates (LA/C L) and small local authorities minus small corporates (LA/C S). $Mkt_{j,t}$ is the return on the relevant benchmark market 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). $sMkt$ ($sLiq$) denotes the sum of contemporaneous and lagged betas (gammas). The regression is at monthly frequency for the 2008-2012 period. R^2s denote the adjusted R-squared. 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. 'Con' is the constant term in the regression, 'CA' refers to cash/alternatives and 'UK IL' refers to UK index-linked bonds.