When Cash Flows Turn Negative: Liquidity-Driven Selling by Pension Funds*

Aleksandar Andonov
University of Amsterdam
and CEPR

Kristy A.E. Jansen
University of Southern California,
Marshall School of Business,
CEPR, and DNB

Joshua D. Rauh
Stanford GSB, Hoover
Institution, and NBER

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Abstract

U.S. public pension funds are long-horizon investors with predictable liability structures. As such, they are often perceived as contrarian investors who can absorb supply shocks and stabilize markets. However, they increasingly face negative net operating cash flows as benefit payments exceed contributions. Using aggregate pension fund data combined with granular holdings obtained through public records requests, we document three findings that challenge the conventional view of U.S. pension funds as stabilizing investors. First, pension funds with more negative cash flows do not incorporate this factor into their target asset allocation, and they maintain low allocation to safe and liquid assets. Second, because of these limited safe asset buffers, pension funds meet cash flow shocks primarily by selling equities. Pension funds absorb \$0.67 per dollar of shock through equity sales. At the security level, pension funds sell across equities and do not follow a liquid-assets-first approach. Third, these equity sales occur even during periods of negative equity returns, indicating they are driven by cash flow needs rather than portfolio rebalancing considerations. Together, these findings show that pension funds have become regular sellers in equity markets rather than contrarian, stabilizing investors.

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1 Introduction

Pension funds are long-horizon investors with predictable liability structures. As such, they are often perceived as insulated from the pressure to adjust portfolios in response to short-term market fluctuations (e.g., Campbell and Viceira, 2002; Cochrane, 2022). They also serve as the classic example of "preferred habitat" investors, with investment horizons aligned to the duration of their liabilities and demand that is price-elastic (Vayanos and Vila, 2021). Consequently, much of the finance literature considers pension funds as long-term investors who can act as liquidity providers in financial markets by absorbing supply shocks and purchasing assets when other market participants are forced to sell (e.g., Greenwood and Vayanos, 2014; Timmer, 2018).

Yet this view rests on assumptions that may not hold for much of the sector. Despite the long-term duration of their liabilities, we document that most U.S. public pension funds experience persistent negative operating cash flows. That is, their inflows from contributions are smaller than their outflows for benefit payments. In principle, funds could anticipate these needs in their strategic asset allocation. If they do not, however, negative cash flows may force asset sales and make pension funds liquidity demanders precisely when the conventional view suggests they should be liquidity providers.

This paper studies how pension funds incorporate negative cash flows ex ante into target asset allocations and ex post into investment decisions. We establish three main findings. First, pension funds with more negative cash flows do not adjust their target asset allocations toward safer and more liquid assets. This is contrary to standard portfolio predictions based on life-cycle considerations, payout needs, or liability hedging (e.g., Sharpe and Tint, 1990; Viceira, 2001; Cocco, Gomes, and Maenhout, 2005; Campbell, Stein, and Wu, 2026). Second, because they maintain limited safe asset buffers, pension funds meet cash flow shocks primarily by selling equities rather than drawing on these safe asset buffers. Third, these equity sales occur even during periods of negative equity

returns, indicating they are driven by cash flow needs rather than portfolio rebalancing (Parker, Schoar, and Sun, 2023; Harvey, Mazzoleni, and Melone, 2025). Together, these findings show that pension funds have become regular sellers in equity markets, challenging the conventional view of pension funds as contrarian, stabilizing investors.

Our study uses a newly constructed dataset of U.S. public pension funds that combines aggregate data on pension fund asset allocation and cash flows with granular holdings data obtained through public records requests. The aggregate sample covers 186 pension funds over 2001–2023, representing 93% of U.S. state and local pension assets. For a subset of 65 pension funds that cover approximately 47% of total pension assets, our public records data provides detailed quarterly holdings across equities, fixed income, cash, alternatives, and derivatives, allowing us to study how funds adjust portfolios at a more granular level when facing cash flow shocks.

Pension fund net operating cash flows are defined as the difference between contribution inflows and outflows for benefit payments and administrative expenditures, scaled by total assets. The average pension fund in our sample has net operating cash flows of -2.4% of total assets. We decompose cash flows into predictable (fitted) and residual components by detrending contributions and benefits separately, using robust regressions that reduce the influence of outliers. This decomposition isolates systematic, predictable trends from shocks driven by sudden shifts in payouts or inflows.

We begin by studying whether pension funds incorporate cash flows in their asset allocation decisions. Financial theory suggests they should. Life-cycle and ALM models predict that mature pension funds, with benefit outflows that outweigh contribution inflows, should allocate more to safe fixed income assets (e.g., Sharpe and Tint, 1990; Viceira, 2001; Cocco, Gomes, and Maenhout, 2005). Work on the intertemporal budgeting of asset-dependent institutions would suggest that mature pension funds, whose operations rely heavily on financial asset returns, should hold more conservative portfolios (Campbell et al., 2026). This hypothesis implies that pension funds with

larger negative cash flows should have a higher target allocation to cash and safe fixed income, and a lower allocation to illiquid alternatives.

When they face predictable cash outflows, pension funds should then meet those outflows primarily by drawing down their safe asset buffers, i.e., cash and safe fixed income assets. When a pension fund faces unpredictable cash outflows, it should follow a liquid-assets-first approach by selling its most liquid and safest assets first, which are typically cash equivalents and safe bonds (e.g., Ben-David, Franzoni, and Moussawi, 2012; Manconi, Massa, and Yasuda, 2012; Choi, Hoseinzade, Shin, and Tehranian, 2020; Ma, Xiao, and Zeng, 2022; Huang, Jiang, Liu, and Liu, 2025), and only turn to riskier and illiquid assets when safe asset buffers are exhausted.

An alternative hypothesis is that pension funds do not adjust asset allocations to cash flows, since holding liquid assets entails lower expected returns (Wermers, 2000; Lucas and Zeldes, 2009). For pension funds, the opportunity cost of forgoing higher returns on risky assets may outweigh the costs of selling those assets when liquidity needs arise. This trade-off is reinforced by GASB accounting rules. Pension funds discount their liabilities using the expected rate of return, which discourages holding low-yielding liquid and safe assets (e.g., Novy-Marx and Rauh, 2011; Andonov, Bauer, and Cremers, 2017). Under this hypothesis, operating cash flows do not affect target allocations. Pension funds meet their liquidity needs through *pro-rata selling*, liquidating assets proportionally across asset classes to preserve strategic asset allocations despite differences in liquidity and volatility across assets.

Contrary to the hypothesis that funds facing more negative or volatile cash flows should have large allocations to safe and liquid assets, we find no relation between cash flows and target allocations, either across funds or within funds over time. Even when focusing only on the predictable component of operating cash flows, pension funds with lower predictable cash flows do not increase allocations to cash and fixed income, nor do they reduce allocations to alternatives. The absence of a statistically

significant relationship is not merely a matter of statistical precision: even the largest point estimates imply economically small allocation changes that are far below the shifts in cash and fixed income allocations prescribed by target-date life-cycle fund glidepaths for comparable differences in participant age and retirement horizon.

Using the holdings data obtained from public records requests, we examine allocations to cash and U.S. Treasuries directly, the least volatile and most liquid assets in pension portfolios. We find no systematic relation between cash flow positions and allocations to these assets. On average, pension funds maintain limited safe asset buffers, with cash and Treasuries representing only 10% of total assets. Despite persistent negative operating cash flows, target allocations do not vary systematically with cash flow exposure. This pattern suggests that pension funds perceive the opportunity cost of holding low-return safe assets as greater than the cost of liquidating risky assets when cash needs arise.

Negative operating cash flows make pension funds regular sellers in financial markets, as they must raise cash to cover benefit payments. We next examine which assets pension funds sell to meet these liquidity needs and whether selling patterns differ between predictable and unexpected cash flows. Our main dependent variables are the investment flows into and out of different asset classes.

We find that pension funds do not respond to predictable negative cash flows in the manner implied by the liquid and safe-assets-first hypothesis, as flows are not concentrated in cash and fixed income. Instead, predictable cash outflows are absorbed through pro-rata flows, though constrained by illiquid alternatives: a $1 predictable outflow leads to sales of $0.35 in cash and fixed income and $0.54 in equities, amounts somewhat above their average target weights. Flows to alternatives are also positive but insignificant, and our results confirm that predictable outflows are spread mainly across fixed income and equity. These results indicate that predictable cash flows do not induce substantial shifts in portfolio composition or risk.

In contrast, responses to unpredictable cash flows are asymmetric and depart from both the liquid and safe-assets-first and pro-rata benchmarks. Pension funds absorb modest positive residual cash inflows through constrained pro-rata investments, with larger inflows directed primarily to cash and fixed income. However, negative residual cash outflows lead to substantial sales of equities ($0.67 per $1) and alternatives ($0.41 per $1), while cash and fixed income remain largely unchanged.[1] Strikingly, this pattern—disproportionate equity sales alongside stable holdings of safe and liquid assets—implies more equity selling than predicted by either hypothesis.

We interpret this deviation from pro-rata selling when facing negative shocks as a reflection of low safe asset buffers. With only about 10% of pension fund assets in cash and U.S. Treasuries, these buffers could be quickly depleted.[2] To test this mechanism, we examine heterogeneity across portfolio composition. We find that pension funds with higher allocations to alternatives absorb negative residual outflows primarily through equity sales, while the effect is insignificant for funds with low allocations to alternatives. Overall, the evidence indicates that limited safe asset buffers are associated with greater reliance on equity sales to meet cash shortfalls.

Using the holdings data assembled from public records requests, we zoom in on the types of equity pension funds sell when faced with negative cash flow shocks. In this part of the analysis, our main dependent variables are the flows into different securities, as opposed to different asset classes. Examining whether pension funds sell fewer illiquid stocks when faced with cash flow shocks allows us to test our hypothesis *within* equities. We define illiquid stocks as those in the top tercile of the Amihud illiquidity measure (Amihud, 2002) or the bottom tercile of market capitalization.

We find that pension funds do not disproportionately sell fewer illiquid stocks when faced with negative cash flow shocks, inconsistent with our hypothesis but consistent with pro-rata flows within

[1]To add to $1, cash and fixed income have a positive coefficient of $0.07 per $1 of residual cash outflow, showing, if anything, an overselling of risk assets and an increase in cash and fixed income balances, though this is not statistically significant.

[2]In addition to benefit payments, pension funds also need liquidity for capital calls on private equity commitments and margin requirements on derivatives.

equities. Using fixed income holdings data, we also confirm that pension funds leave U.S. Treasuries untouched when meeting liquidity needs from operations. Taken together, these patterns imply that pension funds rely on both liquid and illiquid equity sales to meet cash needs, likely incurring nontrivial transaction costs.

Our main cash flow measure focuses on operating cash flows and excludes income from investment activities such as dividends and interest. This definition better reflects the cash flows that pension funds experience, as most funds invest through external asset managers under contracts that reinvest dividends and interest rather than distribute them, requiring funds to submit redemption requests to meet cash needs. Although investment income can provide cash without asset sales, it is insufficient to meet these needs. Even when we add investment income, the combined operating and investment cash flows turn negative after 2008 and average around –1% of assets, leaving shortfalls that require asset sales. Consistent with this, controlling for investment income does not affect our main results: negative residual cash flow shocks continue to generate sales of equities and alternatives. Using the public records holdings data, we find no evidence that funds with greater cash flow pressures tilt toward higher-income securities, such as stocks that pay higher dividends or bonds that pay higher coupons.

The liquidity-driven flows induced by negative cash flows differ significantly from rebalancing flows driven by market movements. To separate rebalancing flows, we control for the lagged allocation gap and time fixed effects. The allocation gap captures pension funds' gradual adjustments of actual allocation weights toward evolving target weights (Andonov and Rauh, 2022; Begenau, Liang, and Siriwardane, 2026), while time fixed effects absorb differences in relative returns across asset classes (Parker, Schoar, and Sun, 2023; Harvey, Mazzoleni, and Melone, 2025; Foley-Fisher and Lee, 2025). Both rebalancing control variables are statistically significant and economically meaningful, with allocation gap coefficients implying partial adjustment of roughly 0.3-0.4 per year, but the coefficients

on predictable and residual cash flows are robust.

We further disentangle cash-flow-driven from rebalancing flows by splitting the sample based on relative equity and fixed income performance. Under a rebalancing (contrarian) motive, investors should not sell equity when equity underperforms fixed income. Instead, we find that equity sales associated with negative cash flows persist across market conditions. Even in periods when equity underperforms fixed income, a \$1 residual cash outflow leads to \$0.63 equity sales, a pattern difficult to reconcile with rebalancing. Moreover, we show that after the Global Financial Crisis, pension funds sold equities in every quarter with negative stock market returns. Taken together, these results indicate that cash-flow shocks generate flows that are distinct from, and not explained by, rebalancing behavior, with shortfalls absorbed primarily through equity sales in both good and bad times.

Overall, our findings provide convincing evidence that pension funds are predictable net sellers in equity markets. This rejects the view of pension funds as long-horizon investors insulated from short-term market fluctuations, as they sell equities even when equities underperform relative to other asset classes. While our empirical analysis focuses on U.S. public pension funds, we show that negative cash flows are also present among other mature long-horizon institutions, including Canadian public pension funds and U.S. university endowments. This suggests that the liquidity pressures we study may extend beyond U.S. public pension funds.

Our paper contributes to the literature on investment decisions by public U.S. public pension funds (e.g., Lucas and Zeldes, 2009; Hochberg and Rauh, 2013; Andonov et al., 2017; Lu et al., 2019; Begenau et al., 2026). The key innovation of our study is that we focus on their operating cash flows and examine how pension fund manage their liquidity needs. Our analysis does not solely rely on aggregate asset allocations. Rather, we obtain an holistic overview of their investment decisions with security-level data on all asset classes, including equities, fixed income, cash, alternative assets,

and derivatives.

Our paper also contributes to the literature that shows long-term investors act as stabilizers in financial markets, because they do not have to sell in times of crises (e.g., Timmer, 2018; Chodorow-Reich et al., 2021; Coppola, 2025; Zhou, 2024). More generally, the literature on investors' horizons suggests that long-horizon investors are less likely to amplify market stress than short-horizon investors, who tend to demand liquidity and intensify price pressure during downturns (Cella et al., 2013). However, our paper shows that there are other times during which long-term investors have to sell and do not act as market stabilizers. Exceptions are Pinter (2023); Pinter et al. (2026); Jansen et al. (2026); Alfaro et al. (2024), who show for European pension funds that forced sales of (safe) assets due to large margin calls on derivative positions can have profound market impact. We show that U.S. public pension funds rely substantially less on derivatives, but we find that liquidity issues arise from other sources, most importantly shocks to pension fund contributions in the presence of large allocations to alternative assets and low safe asset buffers.

Finally, we contribute to the growing demand-based asset pricing literature which studies the equilibrium relation between prices and holdings or flows (e.g., Koijen and Yogo, 2019; Gabaix and Koijen, 2023). While the vast majority of papers in this literature studies all investor types simultaneously (e.g. Koijen et al., 2021; Jansen, 2025; Eren et al., 2026; Bretscher et al., 2026; Fang et al., 2025), several recent papers aim to understand and better micro-found asset demand for specific sectors, such as households (Gabaix et al., 2023, 2025) or target date funds (Parker et al., 2023). In contrast, we focus on understanding the drivers of asset demand for U.S. public pension plans, an important class of institutional investors that has been understudied due to the past scarcity of comprehensive data on their holdings.

2 Institutional Background and Conceptual Framework

2.1 Pension Fund Cash Flows

We study how pension funds incorporate operating cash flows in their investment decisions. For defined benefit pension funds, the operating cash flows consist of contribution inflows and benefit outflows (as well as administrative costs).

On the contribution side, actuarial determinations provide formal grounding. In principle, employer contributions equal the sum of a "normal cost" (the actuarially determined value of benefits accrued during the year as a percentage of salary) and an amortization payment toward any unfunded liability. However, in practice, states and local pension funds differ widely in both the extent to which they adhere to actuarially determined contributions (ADCs) and the assumptions underlying ADCs, such as discount rates and amortization periods.

Some retirement systems, such as Wisconsin and New York State, consistently pay contributions at or near a full ADC calculated on a rigorous basis and have maintained strong funded status over time. Others, such as Illinois and New Jersey, have frequently made contributions set by statute or the budgetary process at levels below actuarial recommendations, with the cumulative effect of producing large unfunded liabilities. Political institutions, and in many instances political discretion, thus play a central role in determining contribution levels. Since no federal funding standard governs state and local systems, contributions ultimately reflect the interaction of actuarial practice, statutory design, and fiscal capacity.

Pension benefit payments are considerably less flexible, as they are determined by employee contracts. Typically, those contracts specify the benefits as a function of years of service and a final or average salary. Still, state and local governments often retain some discretion that affects near-term benefit payments. For example, while many pension funds have cost of living adjustments

(COLAs) determined by formula, in others COLAs are determined periodically by the legislature. Moreover, waves of either more or fewer retirements, driven by economic conditions or employer incentives, can also generate variation in benefit outflows.[3]

2.2 Hypotheses about Target Asset Allocation and Investment Flows

Predictions about pension fund asset allocation begin with standard portfolio theory for long-term investors. To the extent that the role of public pension funds is to meet liability payouts, in an ALM framework the objective is to minimize deviations between assets and liabilities. While it is well known that the governance structures of U.S. public pension funds disincentivize the consideration of ALM (Novy-Marx and Rauh, 2011), our focus is on how pension funds handle the liquidity demands of their operating cash flows.

Financial theory suggests that an investor's risk-taking should align with its ability to adjust cash flows (spending) to changes in financial market conditions (Campbell and Viceira, 2002; Ang, Papanikolaou, and Westerfield, 2014; Jansen and Werker, 2022). This view implies that pension funds with larger negative cash flows or a higher volatility of cash flows should have a higher target allocation to cash and safe fixed income assets, and a lower allocation to illiquid alternatives.[4]

Hypothesis 1. Liquidity Buffer Hypothesis. *Pension funds with larger negative cash flows or a higher volatility of cash flows should have a higher target allocation to cash and safe fixed income assets.*

Three strands of the literature specific to pension funds further motivate this hypothesis. First, life-cycle models suggest that mature pension funds, with benefit outflows that outweigh contribution

[3]In addition, some pension funds can retroactively change the benefits formula. For example, California Senate Bill No. 400 for CalPERS and Chapter 133, Public Law of 2001, for New Jersey increased pensions retroactively.

[4]Alternatives, such as private equity funds, are typically managed in closed-end structures with limited exit options before the end of the fund life. Secondary-market sales are subject to discounts. Even somewhat more liquid alternative assets, such as hedge funds, require a longer time to meet withdrawal requests and can impose redemption gates in stress periods.

inflows, should allocate more to safe fixed income assets. These models imply that mature funds should reduce the equity share as the value of labor income of their average participant declines (e.g., Merton, 1971; Viceira, 2001; Cocco, Gomes, and Maenhout, 2005; Gomes and Michaelides, 2005; Dahlquist, Setty, and Vestman, 2018). For example target date funds, which are designed based on life-cycle investment principles, implement a substantial shift toward fixed income as participants age. Online Appendix Table A.1 shows that the target weight in fixed income assets is 48-60% for someone retiring today, compared with 38-44% for someone retiring in 5 years and 19-23% for someone retiring in 15 years.

Second, even though U.S. public pension funds do not implement ALM models to hedge liabilities, they regularly commission asset-liability studies to design target allocations. In an ALM setting, equities may be attractive for younger pension funds because future benefits depend on wage growth, which is positively correlated with stock returns over longer horizons (Lucas and Zeldes, 2006). However, as equities are long-duration assets, pension funds would be expected to reduce the equity share as they mature and move toward short-term safe assets, which more closely replicate their liabilities (e.g., Sharpe and Tint, 1990; Hoevenaars, Molenaar, Schotman, and Steenkamp, 2008; Jansen, 2025).

Third, the research on intertemporal budgeting of asset-dependent institutions argues that mature pension funds are more asset-dependent in their operations and should hold a conservative portfolio (Campbell et al., 2026). Keeping a buffer of safe and liquid assets would help these funds reduce the probability of forced sales of illiquid long-term assets and the likelihood of insolvency (Scholes, 2000; Duffie and Ziegler, 2003).

Hypothesis 2(a). Safe Asset Buffer Draws. *In response to predictable cash outflows, pension funds draw down on their safe asset buffers.*

Following directly on Hypothesis 1, the implication is that predictable cash outflows should be

met using the assets that pension funds are already holding to meet cash flows. Pension funds facing predictable outflows should therefore meet those outflows primarily by drawing down their safe and liquid asset buffers, i.e., cash and safe fixed income assets.

Hypothesis 2(b). Liquid Asset First. *In response to unpredictable cash outflows, pension funds follow a liquid-first approach by selling their safer and most liquid assets first, and only turn to riskier and illiquid assets when liquidity buffers are exhausted.*

When a pension fund faces unpredictable cash flow shocks, they should liquidate their safer and most liquid assets first and turn to riskier and illiquid assets only if shocks exceed available buffers. Thus, pension funds follow a liquid-asset-first approach by selling their safest and most liquid assets first, which are typically cash equivalents and safe bonds (e.g., Ben-David, Franzoni, and Moussawi, 2012; Manconi, Massa, and Yasuda, 2012; Choi, Hoseinzade, Shin, and Tehranian, 2020; Ma, Xiao, and Zeng, 2022; Jansen, Klingler, Ranaldo, and Duijm, 2026; Huang, Jiang, Liu, and Liu, 2025), while equities and alternatives remain largely untouched. This strategy minimizes trading costs and the likelihood of having to sell at depressed prices.

Hypothesis 3. Pension Funds as Shock Absorbers. *Pension funds, as long-horizon institutional investors, supply liquidity and absorb shocks.*

This hypothesis follows the common view that pension funds, as long-horizon investors with predictable liabilities, should act as stabilizers during periods of market stress because they do not have to sell (e.g., Chodorow-Reich et al., 2021; Zhou, 2024; Coppola, 2025). Indeed, their benefit payments are often modeled as stable and largely insensitive to short-term market fluctuations (e.g., Campbell and Viceira, 2002; Cochrane, 2022). Moreover, if they maintain sizable safe asset buffers as argued in Hypothesis 1, they may even engage in countercyclical rebalancing by purchasing risky assets when prices fall (e.g., Timmer, 2018; Harvey et al., 2025).

An alternative hypothesis is that pension funds, even when facing persistent negative cash flows, have little incentive to maintain a higher target allocation to safe and liquid assets, because cash delivers lower expected returns (Wermers, 2000). More generally, corporate liquidity and risk management models emphasize that optimal liquidity management trades off the opportunity cost of holding liquid assets against the cost of raising cash when liquidity is low. These models imply that low safe asset buffers need not be inefficient when cash needs are predictable and assets can be sold at low cost, but larger buffers become more valuable when cash shortfalls coincide with states in which asset sales are especially costly (Froot et al., 1993; Bolton et al., 2011). Pension funds may therefore perceive that the cost of forgoing higher returns on risky assets outweighs the costs of selling those assets when liquidity needs arise. Moreover, investing more in risky assets may reduce the expected burden on taxpayers (Lucas and Zeldes, 2009).

This trade-off is reinforced by the institutional and political context of public pension fund accounting. Under GASB guidelines, pension funds discount their liabilities using the expected rate of return, which directly affects reported funding status. Consequently, pension fund boards, which are often composed of political appointees and employee representatives, set high expected returns (e.g., Novy-Marx and Rauh, 2011; Andonov, Bauer, and Cremers, 2017), and pension CIOs are tasked with designing portfolios that could meet them. The resulting incentive structure discourages holding low-yielding liquid and safe assets. Under this hypothesis, operating cash flows generally would not affect pension fund target asset allocation. Instead, pension funds meet liquidity needs through pro-rata selling, whereby they liquidate assets proportionally across asset classes to preserve target allocations.

In practice, pro-rata selling may be constrained by the significant costs of selling illiquid alternative assets, such as private equity and private real estate. Predictable cash-flow-driven sales will then lead to investment flows that are roughly proportional to the asset class portfolio weights, but with

adjustments concentrated in fixed income and public equity.

3 Data on Pension Fund Cash Flows and Assets

Our paper merges data from several sources to obtain a comprehensive overview of U.S. public pension funds' balance sheets, cash flows, and assets. We describe the aggregate pension fund data in Section 3.1, and the holdings data obtained through public records requests in Section 3.2.

3.1 Aggregate Pension Fund Data

Our analysis focuses on the asset allocation decisions of U.S. public pension funds. The unit of observation at the pension fund (retirement system) level. We aggregate asset allocation and performance data across all pension plans that are managed collectively at the pension fund level. For instance, the New Jersey Division of Investment is responsible for the asset management of multiple pension plans—including New Jersey PERS, New Jersey Police & Fire, and New Jersey Teachers—and we aggregate the data across these plans. Our aggregation also accounts for mergers of pension funds over time.[5]

Our sample covers 186 U.S. public pension funds over the 2001–2023 period. We construct the dataset using two sources. First, the Public Plans Database (PPD) provides data for 145 pension funds (3,240 annual observations). Second, we supplement this data with hand-collected data on 41 local county and city pension funds (843 annual observations) that are not included in the PPD. Collectively, these pension funds managed $5.0 trillion of assets in 2023, which is more than 93% of all public DB pension assets.[6] From these sources, we obtain information on pension fund size, cash flows, actual and target asset allocations, performance, and other characteristics.

[5]For example, Indiana PERF and Indiana Teachers operated as separate pension funds until 2011. In 2012, the two funds were merged into the newly established Indiana Public Retirement System.

[6]The U.S. Financial Accounts show that state and local pension funds managed $5.37 trillion in assets in June 2023.

The net operating cash flows for each pension fund are measured as the difference between the total inflows from contribution payments and the total outflows for pension benefit payments and administrative expenditures. *%CF* is the ratio of net cash flows to pension fund assets under management (AUM) at the beginning of the year.

We use a two-step detrending procedure to decompose the net cash flows into predictable fitted cash flows and residual cash flows. First, using robust regressions that down-weight observations with large absolute residuals (Huber, 1964), we regress the contributions and benefits of each pension fund separately on an annual trend variable to obtain the fitted and residual contributions, and fitted and residual benefits. Second, we estimate the *%CF Fit* as the difference between fitted contributions and fitted benefits scaled by pension assets at the beginning of the year. The *%CF Residual* is the difference between residual contributions and residual benefits scaled by assets.

One limitation of this decomposition is that it incorporates forward-looking information, as we use all observations of each pension fund in the detrending of contributions and benefits. In the context of defined-benefit pension funds, the forward-looking assumption is plausible as the main determinant of the net cash flows is the percentage of retired members, so the trend in contributions and benefits can be predicted even over a long horizon. Online Appendix Figure B.1 shows that the predictable *%CF Fit* component of net cash flows is negatively correlated with the percentage of retired participants, while the *%CF Residual* component and the percentage of retired participants are uncorrelated.

Nevertheless, as a robustness, we construct an alternative decomposition of *%CF* into *%CF Predicted* and *%CF Shock*. We estimate robust regressions of the contributions and benefits of pension fund i over the period from $t-10$ to $t-1$, and use the fitted values to predict the contributions and benefits in year t. *%CF Predicted* is the difference between the predicted contributions and benefits scaled by pension assets at the beginning of the year. *%CF Shock* is estimated using the differences

between the realized contributions (benefits) and the predicted contributions (benefits). While this decomposition does not use forward-looking information, it does reduce the sample coverage over time, and we cannot analyze the pension fund cash flows around the global financial crisis.

Online Appendix Table B.1 shows that both decompositions deliver highly correlated estimations. The *%CF Fit* and *%CF Predicted* measures have a correlation of 0.87, and both are highly correlated with the baseline *%CF* measure. In the paper, we use the decomposition of cash flows into *%CF Fit* and *%CF Residuals* in the main analysis, as it retains the full sample, and use the decomposition of cash flows into *%CF Predicted* and *%CF Shock* in robustness tests.

Figure 1 Panel A shows that U.S. public pension funds are mature, as their inflows from contributions are smaller than their outflows for benefit payments and administrative expenditures. The average pension fund-year observation has negative net operating cash flows of around 2.4%. The net cash flows vary substantially over time and across pension funds as the 5^{th} percentile of funds receives negative cash flows of around 7% of total assets, while the 95^{th} percentile of funds receives positive cash flows of around 1% of total assets.

Online Appendix Figure H.1 shows that negative cash flows are also present among other long-horizon institutional investors: Canadian public pension funds have moved from positive toward negative net cash flows over 2014–2023, and U.S. university endowments have persistently negative cash flows close to the magnitude we observe for U.S. public pension funds.

Table 1 shows that the predictable *%CF Fit* accounts for the level of negative cash flows, given very similar means of *%CF* and *%CF Fit*. However, the *%CF Residual* component has a substantial standard deviation of 2.8%. Figure 1 Panel B shows that the residual cash flows vary substantially over time, with pension funds facing positive and negative cash flows over the entire sample period. Panels C and D present the residual detrended contributions and benefits. The variation in *%CF Residual* comes primarily from substantial deviations from the trend of contribution inflows, while

the benefit payments are much more predictable. Online Appendix Table B.2 presents 10 examples of pension funds experiencing extreme positive and negative residual cash flows. It shows that positive residual cash flows are due to high contribution inflows, and they are financed either from general reserves and revenue or by issuing a pension obligation bond. Negative residual cash flows occur mostly due to low contribution inflows significantly below the actuarially required contributions, but sometimes also due to high outflows to pay for plan transfers and lump sum withdrawals.

For both actual and target asset allocations, we follow the data adjustments outlined by Andonov, Bonetti, and Stefanescu (2025) and Begenau, Liang, and Siriwardane (2026) to enhance the consistency of the PPD data. These adjustments account for misclassified asset categories, missing allocation data, mismatches between target and actual allocation categories, and the treatment of leverage—specifically, the failure to classify leverage as a negative allocation to cash. Panel C of Table 1 shows that the average pension fund-year observation has a target asset allocation of 50.5% to public equity, 25.6% to fixed income, 9.9% to real assets, 6.9% to private equity, and 4.9% to hedge funds. The remaining part is allocated to cash or other risky assets. Other risky assets include undifferentiated broad portfolios of alternative assets and other assets.

3.2 Holdings Data: Public Records

There is no publicly available dataset on pension fund holdings, even though their participants cannot choose whether to join the pension system, and the taxpaying public is largely liable for unfunded liabilities. Other institutional investors, such as mutual funds and insurance companies, need to frequently disclose their holdings, but pension funds are not covered by any regulatory disclosure requirements. The 13F dataset is the only publicly available source with some information on pension fund holdings. However, the 13F data covers only the direct U.S. equity holdings of pension funds, so all their domestic and international equity holdings that are managed through

external asset managers cannot be identified and studied. In addition, there is no information on their fixed income holdings, derivatives positions, and commitments to private funds.

To obtain a comprehensive and granular overview of pension funds' investments, we collect detailed holdings data on their investments through public records requests. Specifically, we have asked U.S. public pension funds about their equity, cash, fixed income, alternatives, and derivatives positions on a quarterly basis over the 2000–2023 period.

We contacted a total of 178 pension funds and received responses from 151 of them. Out of these responses, 26 pension funds denied our request to deliver data and 3 pension funds demanded a processing fee that we deemed too high.[7] We thus ended up with 122 pension funds that delivered data to us.

Unfortunately, many pension funds delivered incomplete data, such as references to annual summaries of the investments on their websites, annual rather than quarterly holdings data, many missing quarters, or total holdings that did not line up with the aggregate asset class information that we obtained from PPD. We therefore classified a fulfilled request as successful if (i) the pension fund provided quarterly data for at least a period of five years; (ii) delivered data on all asset classes, with the exception of alternative assets;[8] (iii) the total allocation to different asset classes line up with the PPD database described in Section 3.1. To date, a total of 65 pension satisfy these criteria. We provide a detailed overview of the procedure of making public records request in Appendix C.1.

Figure 2 shows the number of pension funds we cover in each period, together with the total assets over time. In 2021, the public records subsample covered $2.4 trillion in total assets, which corresponds to approximately 47% of the total assets of $5.1 trillion held by U.S. public pension plans. Appendix Figure C.1 shows that the coverage of the public records database is well-distributed across states. Additionally, Appendix Table C.1 shows that there is no relationship between pension

[7]These three pension funds informed us that the quarterly data for one year would amount to $5,000, which would imply $120,000 for the full sample period.

[8]Some pension funds were exempt by state regulation from sharing their alternative asset holdings with us.

fund cash flows and the likelihood of disclosing holdings data through public records requests. The only notable pension fund characteristic that raises the probability of disclosure is pension fund size, while the holdings disclosure is unrelated to pension funding status, performance, and asset allocation.

Figure 3 shows the detailed cross-sectional average asset allocation of pension funds in our public records sample over time. The trends in the holdings data are consistent with those observed in the aggregate pension data and documented in prior research (e.g., Andonov and Rauh, 2022; Begenau, Liang, and Siriwardane, 2026): a rise in the allocation to alternatives from 6% in 2000 to 32% by the end of our sample period, offset by declines in equity and fixed income holdings. Moreover, the holdings data enable us to document that the total liquid asset holdings, defined as cash and U.S. Treasuries, are rather limited, amounting to just 10% of total assets.

Table 2 summarizes the public records data in greater detail. The first three columns report statistics about the average number of positions that pension funds have in each asset class.[9] On average, pension funds have 3,771 equity positions, while this equals 2,135 for fixed income. The average number of positions is lower in alternative assets, amounting to 260.[10] Turning to the next three columns, we find that pension funds have 2,366 unique securities in equities on average, while this equals 1,873 for fixed income and 188 for alternatives. This suggests that pension funds invest in the same stock across multiple accounts, each exploiting different strategies. The last three columns show the allocations to each detailed asset category, confirming the findings of Figure 3.

Finally, Table 3 summarizes the derivatives data obtained through public records requests. Derivative usage is heterogeneous across pension funds; for instance, 45% of pension fund-quarter observations use equity futures, while 62% use fixed income instruments (including futures, forwards, and swaps), and 43% use currency forwards or swaps. However, despite this heterogeneity, the

[9]The procedure to assign asset classes to each individual position is described in detail in Appendix C.2.

[10]Pension funds disclose only the commitments to private funds, and do not provide information on the underlying buyout, venture capital, or real estate deals financed by these private funds.

economic magnitude of these positions is relatively small. Total gross notional amounts (which reflect the maximum potential exposure since long and short positions do not offset) are limited. For example, the gross notional in equity futures is only 0.1% of total assets on average, and 0% for the median fund.[11] Derivative usage is more substantial within fixed income, with the total gross notional equaling 1.5% of total assets, while for currency derivatives, it is 0.4%. Although 60% of pension fund-quarter observations use options, this usage represents only 0.3% of total assets.

4 Target Asset Allocation

In this section, we examine whether pension funds incorporate operating cash flows in their target asset allocations and holdings of liquid and safe assets. We estimate the following specification:

$$\omega_{i,t} = \beta CF_{i,t} + \Gamma X_{i,t-1} + \theta_t + PF_i + \epsilon_{i,t}, \tag{1}$$

where $\omega_{i,t}$ is the target allocation of pension fund i in year t to cash & fixed income, equity, or alternative assets. $CF_{i,t}$ captures the cash flows. We focus mainly on net operating cash flows ($\%CF$) and fitted cash flows ($\%CF\ Fit$) in the models. $X_{i,t-1}$ is a vector of lagged controls that includes the log of pension fund size and the GASB funding status. θ_t is time fixed effects, defined on a reporting-year level to address differences in fiscal-year ending dates across pension funds. The reporting-year fixed effects capture fluctuations in market returns and macroeconomic conditions. In the models, we either examine cross-sectional variation or include pension fund fixed effects (PF_i) to explore within-fund variation. We cluster the standard errors by pension fund.

In Table 4, we find no relation between cash flows and target allocations. The liquidity buffer hypothesis predicts a negative relation between $\%CF$ and allocation to cash & FI. Contrary to this

[11] For all derivative categories, the common sample contains 47 of the 65 pension funds. We exclude 18 pension funds for which USD notionals cannot be measured consistently, and omit individually unusable fund-quarter observations for otherwise eligible funds. Genuine zero positions are retained.

hypothesis, Columns (1) and (2) of Panel A show that the variation in *%CF* across and within pension funds is not related to the target allocation to cash & FI. In addition, Columns (5) and (6) show that pension funds with lower cash flows do not have a lower allocation to illiquid alternatives.

The *%CF* measure includes predictable cash flows as well as shocks. It may well be that pension funds incorporate the expected component in their allocation policy, but the unpredictable component renders the overall relation insignificant. Panel B addresses this argument by examining the relation between target weights and the *%CF Fit* measure, which considers only the fitted values of contributions and benefits. The results show that pension funds do not incorporate even the expected component of cash flows when designing their target asset allocation policy. In Panel C, we confirm this result further by including the *%CF Predicted* instead of *%CF Fit* measure to capture the expected component of pension fund cash flows. By construction, the *%CF Predicted* measure is available only for the second half of our sample period, and shows that there is no adjustment in the allocations over time, even after many pension funds experienced negative cash flows for a prolonged period of time.

Instead of incorporating the level of *%CF* in their targets, pension funds may focus more on the volatility of cash flows. An alternative interpretation of the liquidity buffer hypothesis is that pension funds with more volatile cash flows need to maintain a larger allocation to liquid and safe assets to absorb the volatility. In Panel D, we measure the relation between the *%CF Volatility* over the previous ten years and target weights. Again, we document that pension funds with more volatile cash flows do not adopt a higher allocation to cash & FI, or at least a lower allocation to illiquid alternative assets.

While the coefficients are statistically insignificant, they are also economically small, suggesting that the absence of meaningful effects is not simply due to limited statistical power. Although, in some specifications, the point estimates have the sign predicted by the safe asset buffer hypothesis

(lower operating cash flows are associated with somewhat higher target allocations to cash and fixed income), the magnitudes remain economically small. For instance, the largest negative estimate we find is -0.19 in Column (2) of Panel B, Table 4, which implies that a one percentage point increase in operating cash outflows is associated with only a 0.19 percentage point increase in the target allocation to cash and fixed income. By contrast, the life-cycle benchmark in Online Appendix Table A.1 implies much larger allocation changes: moving from an average participant age of 50 to 51 is associated with a 1.4 to 3.1 percentage point increase in fixed income allocations. In our sample, pension funds with fitted expected cash flows below the 25th percentile (%CF Fit of -3.7%) have an average participant age of 57.4 years, while funds with fitted expected cash flows above the 75th percentile (%CF Fit of -1.2%) have an average participant age of 53.8 years.[12] Using the TDF glidepath and linearly interpolating between adjacent vintages, this 3.6-year difference in average participant age should translate into 5.5 to 8.2 percentage points higher allocation to cash and fixed income of the more mature pension fund. In contrast, applying our largest estimate of 0.19 to the observed difference in %CF Fit implies an increase of less than 1 percentage point in the allocation to cash and fixed income.

The target-date fund sector provides a useful benchmark for the magnitude of life-cycle shifts in asset allocation, but it is not perfectly comparable to funds in our setting. Target-date funds are DC vehicles organized around relatively homogeneous cohorts with similar retirement horizons, whereas the U.S. public pension funds are DB funds that pool participants of different ages and retirement statuses. We therefore also compare our findings to the Dutch defined benefit pension sector, a €1.6 trillion sector for which we can directly compute the percentage of retired participants ($\%Retired$) and observe allocations to fixed income using publicly available data. Dutch plans at the 80th percentile of $\%Retired = 69.8\%$ allocate 55.8% of assets to fixed income, compared with 49.3% for

[12]The difference in average participant age may appear modest because some public safety pension funds, such as fire and police plans, have substantially earlier retirement ages. These plans can therefore experience negative operating cash flows at younger average participant ages than other pension funds.

the median plan ($\%Retired = 45.8\%$).[13] No comparable pattern emerges, however, for the pension funds in our sample: like for the %CF Fit variable, fixed-income allocations are essentially unchanged across the distribution of $\%Retired$, at 24.7% for plans at the 80th percentile ($\%Retired = 53.2\%$) versus 24.8% for the median plan ($\%Retired = 46.8\%$).[14]

While the hypotheses make predictions about the allocation to liquid safe assets, such as cash, government bonds, and money market funds, pension funds rarely specify the composition of fixed income assets in the target allocations. As Table 1 shows, the median target weight to cash is zero, so our specifications rely on aggregate cash & FI targets. However, using the public records holdings data, we can directly examine whether cash flows are related to the composition of cash and fixed income assets. In Table 5, the dependent variables capture actual allocations to cash and U.S. Treasuries, which are the least volatile and most liquid parts of the pension portfolio.[15] We find that the aggregate cash flows, as well as their predicted component, are not related to the allocation to cash and Treasuries. Online Appendix Table E.1 also shows that our results are robust to separately analyzing the holdings of cash and Treasuries, instead of aggregating them.

In addition to the insignificant relation, the mean dependent variable shows that pension funds in general maintain low liquidity buffers: cash and Treasuries together account for 10.3% of the pension assets. Pension funds need liquidity not only for benefit payments, but also to meet private equity capital calls and margin requirements on derivatives. Pension funds could, in principle, address liquidity needs over the short term by using lines of credit, which were drawn on by university endowments following the global financial crisis (Jansen, Phalippou, and Braun, 2023). However, in pension fund annual reports, investment policy statements, and responses to our public records

[13]The data is publicly available on DNB's statistics data search portal, `https://www.dnb.nl/en/statistics/data-search/`, under the datasets "Individual pension fund data (quarterly)" and "Individual pension fund data (annual)".

[14]We restrict both samples to the overlapping 2017–2023 period to ensure comparability across countries.

[15]We exclude pension fund fixed effects from these specifications because the public records holdings sample is weighted toward the latter part of the sample period, leaving limited within-fund time-series variation. As a result, %CF Fit is nearly collinear with the pension fund fixed effect.

requests, we find no evidence that pension funds rely on lines of credit to manage cash flows and smooth their liquidity needs.

Overall, pension funds decide on the target weights and appropriate level of risk largely independent of their operating cash flows. Funds with negative operating cash flows do not have a higher target allocation to cash and fixed income assets, nor do they reduce the allocation to illiquid alternative assets. The results align with the hypothesis that pension funds perceive the cost of forgoing higher returns on risky assets as greater than the cost of liquidating risky assets when cash needs arise.

5 Pension Fund Aggregate Flows

Negative operating cash flows make pension funds regular sellers in financial markets, as they must raise cash to cover benefit payments. This section examines which assets pension funds sell to meet these liquidity needs and whether selling patterns differ between predictable and unexpected cash flows. Our main dependent variable is the investment flow of pension fund i into asset class j in year t:

$$Flow_{i,j,t} = \frac{A_{i,j,t} - A_{i,j,t-1} \times (1 + R^{BM}_{j,t})}{TA_{i,t-1}} \tag{2}$$

where $A_{i,j,t}$ is the dollar amount invested by pension fund i in asset class j in year t. $TA_{i,t-1}$ is the total amount of assets under management. $R^{BM}_{j,t}$ is the median return of all pension funds that operate with the same fiscal year end in asset class j in year t. We use the median return because not all pension funds consistently disclose returns by asset class in their reports and in the PPD dataset. We construct flows for seven asset classes: cash, fixed income, equity, private equity, real estate, hedge funds, and other risky assets. For our analysis, we aggregate flows into cash and fixed income, and into alternatives (private equity, real estate, hedge funds, and other risky assets).

To examine how pension fund cash flows affect investment flows by asset class, we estimate the following specification:

$$Flow_{i,t} = \beta CF_{i,t} + \Gamma X_{i,t-1} + \theta_t + PF_i + \epsilon_{i,t}, \tag{3}$$

where $Flow_{i,t}$ is the investment flow of pension fund i in year t to cash & fixed income, equity, or alternative assets. $CF_{i,t}$ captures the cash flows. We focus mainly on fitted and residual cash flows in the models. $X_{i,t-1}$ is a vector of lagged controls that includes the log of pension fund size, GASB funding status, and allocation gap. The lagged allocation gap, defined as $(\omega_{i,j,t-1}^{Target} - \omega_{i,j,t-1}^{Actual})$, measures the difference between the pension fund's target and actual allocation in asset class j. This variable controls for rebalancing flows that aim to reduce deviations from target weights. θ_t is time fixed effects, defined on a reporting-year level. The reporting-year fixed effects absorb common shocks to asset class returns and macroeconomic conditions, e.g., periods when equities outperform bonds or vice versa, that could generate similar rebalancing flows across all pension funds. In the models, we also include pension fund fixed effects and cluster the standard errors by pension fund.

In Table 6, we find that pension funds do not respond to the negative cash flows in line with the liquid-asset-first hypothesis as the flows are not highly concentrated in cash and fixed income. To the predictable cash flow component (*%CF Fit*), pension funds respond with constrained pro-rata flows. Based on Columns (1) and (3), \$1 of predictable cash outflows is absorbed by selling \$0.35 of cash & FI, and \$0.54 of equities. These amounts are close to the average target weights to these asset classes presented in Table 1. The flows to alternatives are positive, but statistically insignificant, which confirms that the pro-rata selling is constrained as fixed income and equity assets absorb a slightly larger share of the flows. Overall, predictable cash (out)flows do not induce significant shifts in major asset class weights and do not make pension fund portfolios relatively riskier.

We examine how pension funds adjust to unpredictable cash flows by implementing a piecewise decomposition of the *%CF Residuals* variable into $\%CF\ Residual\ Pos_{i,t} = \max(\%CF\ Residual_{i,t},0)$ and $\%CF\ Residual\ Neg_{i,t} = \min(\%CF\ Residual_{i,t},0)$ components. Table 6 shows that pension funds respond asymmetrically to positive and negative cash flows. Their investment flows in response to residual cash flows deviate from both the liquid-asset-first hypothesis and pro-rata selling. Positive residual cash inflows are absorbed mainly by cash and fixed income ($0.78 per $1), with only $0.22 going to equities and $0.04 to alternatives.[16] In contrast, negative residual cash outflows result in sizable sales of equities ($0.67 per $1) and alternatives ($0.41 per $1), while cash and fixed income remain largely unaffected, showing a statistically insignificant negative coefficient of $0.07.

These patterns support the view that pension funds hold limited liquidity buffers and must absorb outflows by selling risky assets. The p-value tests formally confirm that the coefficients on positive and negative residual cash flows are statistically different for all three asset classes. The positive coefficients on equities and alternatives, combined with the muted negative response of cash and fixed income, are consistent with funds selling risky and less-liquid assets more than proportionally during negative residual cash-flow shocks and potentially retaining part of the proceeds in safe and liquid assets as a buffer against (near) future liquidity needs (Brown et al., 2010). Moreover, the selling of equities and alternatives is inconsistent with pension funds revising downward their expected risky asset returns, because in that case we would expect these sales to be accompanied by reductions in target equity and alternative asset allocations. Instead, Section 4 shows that target allocations are unrelated to cash flows.

To make our results concrete, we also provide a case study of the Dallas Police & Fire Pension

[16]Specifically, we find that pension funds absorb modest positive residual cash inflows through constrained pro-rata investments, while they absorb very large residual inflows primarily by cash and fixed income. Institutional frictions help explain this pattern. Most pension funds invest exclusively through external managers. To deploy large inflows of capital, pension funds need to issue a request for proposals (RFPs), evaluate finalists, and obtain board approval to hire a new manager or significantly expand an existing mandate. In line with this, we show in Online Appendix Table D.1 that the large inflow to cash and fixed income after positive cash flow shocks reverts into equity flows the next year.

(DPFP) System Run in Internet Appendix Figure F.1, using FOIA holdings data to examine investment flows at a more granular level. In 2016, DPFP experienced massive Deferred Retirement Option Plan (DROP) withdrawals of over $600 million (Dallas Police & Fire Pension System, 2017), which created cash outflows equaling -26% of total assets, of which 22% was unexpected. To meet these redemption requests, the system primarily liquidated its equity holdings and other risky assets, comprising investment funds and hedge funds, while also selling a smaller amount of fixed income securities. As the run intensified, DPFP further raised liquidity by selling 26 alternative fund investments and seven direct real estate assets (Dallas Police & Fire Pension System, 2017).

Online Appendix Table D.2 reports a robustness test using the decomposition of cash flows into *%CF Predicted* and *%CF Shock*, rather than *%CF Fit* and *%CF Residuals*. This decomposition avoids using forward-looking information, but restricts coverage only to the second half of the sample period. The results confirm that pension funds absorb predictable cash flows proportionally across asset classes, consistent with the pro-rata hypothesis. The results also confirm that cash flow shocks generate asymmetric responses: negative shocks lead to outflows from equities and alternatives, while positive shocks are absorbed largely by safer assets. We also replicate the analysis for the public records subsample of pension funds in Online Appendix Table D.3 and show that our results remain the same.

5.1 Negative Cash Flows and Investment Income

Our main measure only considers the net cash flows from pension fund operations, and does not incorporate the cash flows from investment activity, such as income from dividends and interest payments. This definition of the main cash flow measure better reflects the flows that pension funds experience because the dividends and interest payments are typically not passed through to the pension funds. Most pension funds invest exclusively through external asset managers, and the

standard contractual terms include reinvestment of dividends and interest payments rather than distributing these payments back to the pension fund. Thus, most pension funds need to submit redemption requests to external managers to cover their cash flow shortfalls.

Nevertheless, investment income can be an important source of cash flow that does not require transactions. In Online Appendix Figure B.2, we add the annual income from investment activities to the net cash flow. We consider either a narrower measure of investment income that includes only dividends and interest payments, or a broader measure that also adds cash flows from security lending and other investment activities.[17] Panel A shows that the income from dividends and interest payments has declined from 2.8% in 2001 to 1.8% of pension assets in 2023.[18] Panel B shows that even if these payments were passed through to the pension funds, they would not be sufficient to meet the cash needs at the end of our sample period. For instance, the combined cash flows from operations and investment activity turn negative after 2008 and fluctuate around -1.0% of pension assets. For most pension funds, the investment income is insufficient to cover the average predictable outflows as *%CF Fit* is -2.5%. Any residual negative cash flow shocks add further liquidity demands on top of this baseline.

To validate the robustness of the investment income reported in PPD, we also compute investment income directly from the holdings data. For each pension fund, we aggregate the interest (coupon) and dividend payments received on individual securities, weighting by position size. Panel A of Figure B.3 shows that investment income from holdings averages 1.6% of pension fund assets across years. In the sample of fund-years with both measures available, Panel B shows that the holdings-based measure averages 1.7%, compared with 2.0% in PPD. The two series closely comove, with a correlation of 0.89.

[17]The trend and level of the broader measure match the narrower measure, which confirms that dividends and interest payments are the main source of investment income.

[18]By comparison, the average dividend yield of S&P 500 firms reported in Shiller's data is 1.87% over the 2001–2023 period, which also falls short of covering predictable outflows.

We also use investment income from the holdings data to test whether pension funds with larger cash flow needs hold higher income-paying assets, such as higher dividend-paying equities or higher coupon-paying bonds. We run the same regression as in Table 5, replacing the dependent variable with total investment income (dividends and coupons) relative to total equity and fixed income assets. Table 7 shows that the raw cash flow measure, expected cash flow measures, and cash flow volatility are all unrelated to investment income.[19] Internet Appendix Table E.2 further shows that these conclusions remain unchanged when separately analyzing dividends relative to total equity and coupons relative to total fixed income.

Finally, we examine the robustness of our results on the effect of pension fund cash flows on asset class flows by controlling for the investment income. In Online Appendix Tables D.4 and D.5, we control for the broad and narrow measures of investment income as a percentage of pension assets. While we do observe that the investment income is positively related to the flows in fixed income and equities, the coefficients on residual cash outflows remain unaffected. After controlling for investment income, negative residual cash outflows result in sizable sales of equities and alternatives.

Overall, the aggregate statistics on investment income show that the equity outflows in response to negative cash flows necessarily involve selling assets, as dividends and interest are insufficient to cover the balance. Pension funds with larger cash flow needs do not hold higher paying income assets and the relation between cash flow shocks and investment flows by asset class is also robust to controlling for investment income.

5.2 Negative Cash Flows and Rebalancing

The liquidity-driven flows induced by negative cash flows differ significantly from rebalancing flows driven by market movements. To separate these effects, we include two proxies for rebalancing in

[19] Again, we exclude pension fund fixed effects from these specifications because the public records holdings sample is weighted toward the latter part of the sample period, leaving limited within-fund time-series variation. As a result, %CF Fit is nearly collinear with the pension fund fixed effect.

the specifications. The first proxy, the lagged allocation gap, is more specific to the pension fund setting, and captures pension funds' gradual adjustments toward evolving target allocations over time (Andonov and Rauh, 2022; Begenau, Liang, and Siriwardane, 2026). The second proxy captures differences in relative returns across asset classes, which affect all multi-asset investors who rebalance their portfolios in response to market movements (Parker, Schoar, and Sun, 2023; Harvey, Mazzoleni, and Melone, 2025; Foley-Fisher and Lee, 2025). Both proxies for rebalancing significantly affect pension fund flows, but cash flows remain a distinct determinant of flows.

The lagged allocation gap, defined as $(\omega^{Target}_{i,j,t-1} - \omega^{Actual}_{i,j,t-1})$, predicts significant positive flows in the next year in all asset classes. For instance, Column (4) of Table 6 shows that a one percentage point higher target than actual allocation weight to equity leads to 0.37% additional flows into equity the following year. The convergence magnitude is similar in fixed income and slightly lower in alternatives, as these assets are less liquid.

In our main analysis, we use reporting-year fixed effects to absorb common shocks to asset class returns. The time fixed effects are a more efficient way to control for market movements as pension funds allocate capital to many asset classes, rather than just equity and fixed income. Online Appendix Table D.6 shows that the results are robust to replacing the time fixed effects with the difference in returns between equities and fixed income. The benchmark returns ($R^{BM}_{j,t}$) are the median returns of all pension funds that operate with the same fiscal year end. We find that a 10 percentage point equity–bond return difference is associated with a 0.9% inflow to cash & fixed income and 0.7% outflow from equities. Importantly, the coefficients on predictable and residual cash flows remain the same.

Table 8 aims to further disentangle cash-flow-driven from rebalancing flows. Using the asset class benchmark returns, we split the sample into periods when equity returns are higher than fixed income returns, and vice versa. The rebalancing hypothesis posits that pension funds trade

in a contrarian way by selling recent winners to realign toward target allocations. This hypothesis predicts that pension funds sell outperforming assets, so when fixed income outperforms equity, we should not observe outflows from equity.

However, we find that the liquidity-induced sales due to negative cash flows do not change conditional on market returns. Panel B reports that, especially in periods when equity returns are lower than fixed income returns, pension funds respond asymmetrically to positive and negative residual cash flows. Based on Column (4), in these periods, a \$1 of residual cash outflows is absorbed by selling \$0.63 of equity, while cash and fixed income remain largely unaffected. This relation cannot be reconciled with rebalancing trades.

Finally, Figure 4 visually shows that both the aggregate pension fund industry and the average pension fund sell equities during periods of negative stock market returns. In Panels A and B, we use the public records holdings data to construct quarterly equity flows based on Equation (2) at the security level. The holdings data allow us to study selling behavior at a higher frequency and to use security-level returns to more accurately compute quarterly equity flows. Equity selling during periods of negative returns becomes particularly pronounced after the GFC: both the aggregate industry and the average pension fund are net sellers in 9 of the 11 quarters with negative stock market returns following the GFC. While the holdings sample enables us to estimate more precise and higher-frequency equity flows, it covers a limited number of pension funds at the beginning of our sample period (see Figure 2).

Panels C and D therefore use the full sample of pension funds to estimate annual equity flows, addressing the limited early-period coverage, and confirming that the FOIA sample is representative of the U.S. public pension fund industry. Using the aggregate sample, we also document that pension funds exhibit negative equity flows in every year since 2003.[20]

[20]Since pension funds have different fiscal-year-ends, they do not experience identical equity market returns at reporting dates. Therefore, when estimating the annual equity flows, we use the median return of pension funds that operate with the same fiscal-year-end and shade the bars based on the percentage of pension funds experiencing

The equity flows documented in Panels C and D of Figure 4 reflect four distinct drivers: rebalancing induced by relative returns between equity and fixed income, active portfolio adjustments toward target allocations, liquidity-driven selling induced by negative cash flows, and other factors. To quantify the contribution of each channel, we multiply the estimated coefficients from Online Appendix Table D.6 by the realized values of the corresponding explanatory variables at the pension-fund-year level and then aggregate the predicted contributions across pension funds. This yields four components: (i) the return difference ($R^{BM}_{EQ,t} - R^{BM}_{FI,t}$), capturing rebalancing in response to relative price movements across equity and fixed income; (ii) the allocation gap ($\omega^{Target}_{t-1} - \omega^{Actual}_{t-1}$), capturing active rebalancing toward target allocation weights; (iii) total cash flows (%CF Fit + %CF Residual), capturing liquidity-driven equity sales; and (iv) other factors, which include the contributions of the remaining controls and the residual component. Figure 5 shows that cash flows are the primary driver of the persistent negative equity flows, while the contribution of return-driven rebalancing is more time-varying and closely tracks equity market performance. Consistent with contrarian rebalancing, pension funds sell equities when equity markets outperform fixed income, making the return-driven component negative in bull markets and positive in downturns (Harvey et al., 2025). The rise in allocations to alternatives since the early 2000s (Begenau et al., 2026) is also reflected in the allocation gap, which contributes predominantly negatively throughout the sample as pension funds gradually reduced their target equity weights.

Our findings may appear at odds with those reported in Gabaix and Koijen (2023), who suggest that state and local pension funds were net buyers of public equities during the GFC. While Gabaix and Koijen (2023) rely on Flow of Funds (FoF) data to estimate these flows, we show in Online Appendix G.1 that the discrepancy is largely driven by the FoF assumption that corporate equities encompass both public *and* private equity. We argue that this assumption misclassifies the growth

negative equity returns. In Online Appendix Figure D.1, we estimate annual equity flows separately for pension funds with June and December fiscal-year-ends, instead of aggregating across all pension funds. June and December are the two main reporting dates and cover 94% of the observations.

in private equity allocations around the GFC period as public equity inflows.

Overall, negative cash flows have a distinct effect on pension fund flows from rebalancing, and most of the negative cash flows are absorbed by equity sales in good and bad times.

5.3 Heterogeneity Across Pension Funds

The evidence presented so far is consistent with pension funds deviating from the pro-rata hypothesis due to their low liquidity buffers, which force them to sell equities when facing negative cash flow shocks. To test this mechanism more directly, we examine heterogeneity across pension funds based on their portfolio composition.

We sort funds into tertiles based on their lagged actual allocation to alternative assets, which is the least liquid asset class in the pension portfolio. We hypothesize that pension funds with higher allocation to alternatives rely more on equity sales when facing negative cash flow shocks because they are more liquidity constrained. First, these pension funds hold less liquid assets. Indeed, the correlation between pension funds' allocation to alternatives and their allocation to liquid assets equals -0.12.[21] Second, a high allocation to alternatives, such as private equity and real estate, implies that these pension funds have substantial capital commitments that can be called at the discretion of general partners (Ang, Papanikolaou, and Westerfield, 2014; Gourier, Phalippou, and Westerfield, 2024). Thus, these pension funds need to preserve a larger fraction of their limited liquidity buffer for unpredictable capital calls, and therefore rely more heavily on equity sales to absorb negative cash flows.

Table 9 Panel A, Columns (1) to (4), shows that negative residual cash flows impact equity flows differently across pension fund tertiles. For pension funds with high allocations to alternatives, a \$1 residual cash outflow results in \$0.51 of equity sales, whereas the effect is insignificant for those with

[21]The correlation between the alternative asset allocation and cash holdings equals -0.14, while this equals -0.05 for U.S. Treasury holdings.

low allocations to alternatives. Conversely, Panel B, Columns (1) to (4), indicates that a $1 residual cash outflow leads to $0.66 in cash and fixed income sales for pension funds with low alternative allocations. For high alternative allocations, there is actually a minor $0.20 increase in cash and fixed income holdings. This increase likely stems from public equity and alternative sales exceeding the initial cash flow shock, with the surplus temporarily held in cash. This pattern of surplus cash following asset liquidations is also evident in the Dallas Police & Fire Pension run (Figure F.1).

In addition, Columns (5) to (8) in Panels A and B split pension funds by their lagged actual allocation to risky assets. Risky assets include equity and alternatives, so the remaining categories are cash and fixed income.[22] Consistent with the low liquidity buffer mechanism, pension funds more concentrated in risky assets sell more equities in response to negative shocks. Overall, these results confirm that pension funds with limited liquid holdings absorb cash shortfalls primarily through equity sales.

Throughout our analysis, we control for the funding ratio as it may affect pension funds' investment decisions. Underfunded pension funds have incentives to reach for yield and maintain low liquidity buffers (Becker and Ivashina, 2015; Andonov, Bauer, and Cremers, 2017; Campbell and Sigalov, 2022). This argument implies that underfunded funds may hold more risky assets and rely more on equity sales to absorb negative cash flows. However, sponsors are typically required to make higher amortization contributions to underfunded pension funds, which may increase their operating cash flows and result in higher liquidity buffers in cash and safe fixed income assets.

In addition to controlling for funding status, we examine heterogeneity across pension funds based on their funding ratio. Online Appendix Table D.7 splits pension funds into tertiles based on their lagged GASB funding ratio. The results show similar patterns across low- and high-funded pension funds. In both groups, negative residual cash flow shocks lead to equity sales, while positive

[22]The correlation between risky asset allocations and liquid asset, cash, and U.S. Treasuries holdings equals -0.24, -0.06, and -0.23, respectively.

shocks are primarily absorbed through increases in cash and fixed income holdings. These results suggest that funding status does not substantially affect how pension funds adjust their portfolios to cash flow shocks.

6 Pension Fund Holdings Analysis

In this section, we examine which securities pension funds sell when facing cash flow shocks. Although pension funds hold limited liquidity buffers at the aggregate portfolio level, their holdings within an asset class vary substantially in terms of volatility and liquidity. We hypothesize that, within a given asset class, pension funds follow a liquid-asset-first approach and absorb negative cash flow shocks by selling the most liquid securities first.

To test this hypothesis, we focus on equities, as they absorb the majority of pension flows, and move to regressions at the security level.[23] We follow the same approach as in the previous section, but now calculate Equation (2) by replacing $A_{i,j,t}$ with the dollar amount invested in each security i by pension j at time t and $R^{BM}_{j,t}$ by the security-level return $R_{j,t}$ for each security j.

We merge pension funds' holdings with public databases to obtain detailed security-level returns.[24] For U.S. stocks, we use the CRSP U.S. Stock Database; for global stocks, the Compustat Global Security Daily Database; and for U.S. Treasuries, the CRSP U.S. Treasury and Inflation Series.

When the securities are not available in CRSP or Compustat, we assume the stock earned the benchmark return: the Russell 3000 Index for U.S. equities and the MSCI ACWI ex U.S. Index for international equities. For bonds other than U.S. Treasuries, we use the Bloomberg U.S.

[23] We omit $\%CF\ Fit$ in this part of the analysis, because the FOIA dataset is concentrated in the latter half of the sample. In this case, the fitted cash flows primarily capture persistent differences across pension funds, which are already absorbed by the pension fund fixed effects. Indeed, Table D.3 shows that a replication of Table 6 for our FOIA sample renders $\%CF\ Fit$ insignificant across asset classes.

[24] The majority of pension funds report ISIN and CUSIP identifiers directly. When these are not reported, we match equity securities by name to obtain the corresponding ISIN or CUSIP, see Appendix C.3. For U.S. Treasury holdings without a successful CUSIP return match, we match to CRSP using the reporting quarter, maturity month, and coupon.

Mortgage-Backed Securities (MBS) Index for mortgage-backed securities, the Bloomberg Global Aggregate Bond Index for global bonds, and the Bloomberg U.S. Corporate Bond Index for U.S. corporate bonds and other U.S. fixed income.

To test how cash flows affect the flows in each security, we estimate the following specification:

$$Flow_{i,j,t} = \beta CF_{i,t} \times Illiquid_{j,t} + \Gamma X_{i,t-1} + \theta_{j,t} + PF_{i,t} + \epsilon_{i,j,t}, \tag{4}$$

where $Flow_{i,j,t}$ is the investment flow of pension fund i in reporting year t to security j: $Flow_{i,j,t} = \sum_{q=1}^{4} \frac{A_{i,j,tq} - A_{i,j,tq-1} \times (1+R_{j,tq})}{TA_{i,tq-1}}$, where the four quarters end at pension fund i's reporting date. We interact the cash flows $CF_{i,t}$ with several security-level indicators that measure the illiquidity of the security ($Illiquid_{j,t}$). Additionally, we control for security-time fixed effects $\theta_{j,t}$. This means that any time-varying characteristics of security j, such as its return, volatility, issuance activity, or credit rating changes, are held constant within that reporting year. We also include fund-time fixed effects $PF_{i,t}$. In practice, these fixed effects ensure that identification of the interaction between pension fund cash flows $CF_{i,t}$ and the illiquidity indicator $Illiquid_{j,t}$ comes only from within-security, cross-fund variation in flows. Finally, we cluster standard errors at the fund and security level.

In our analysis of equity holdings, we estimate $Illiquid_{j,t}$ using the Amihud measure as a proxy for liquidity (Amihud, 2002). The Amihud measure is defined as the average ratio of the absolute return to the trading volume on a given day:

$$\text{Amihud}_{i,t} \;=\; \frac{1}{D_t} \sum_{d=1}^{D_t} \frac{|R_{i,d,t}|}{\text{Vol}_{i,d,t}}, \tag{5}$$

where $R_{i,d,t}$ is the return on stock i on day d in period t, $\text{Vol}_{i,d,t}$ is the dollar trading volume of stock i on day d, and D_t is the number of trading days in period t. We take the average daily Amihud measure over each year. In the regression, we take the top tercile of the Amihud measure as our

$Illiquid_{j,t}$ indicator. As an alternative measure, we take the bottom tercile of the market value of equity (MVE) of the stock as an indicator for illiquid stocks.

Columns (1) and (2) in Panel A of Table 10 show positive, but statistically insignificant, point estimates for the purchases of liquid equities following cash flow shocks. The interaction terms with the Amihud measure are also statistically insignificant in Columns (1) and (2). Columns (4) to (6) show the same pattern when separating positive and negative cash flow shocks: pension funds are not less likely to sell illiquid stocks when facing negative cash flow shocks. We draw the same conclusion when using MVE as a measure of liquidity in Panel B.

We also study whether pension funds sell more U.S. Treasuries within their portfolio of fixed income assets, as arguably, U.S. Treasuries are the most liquid part of their portfolio. We therefore rerun model (4) for fixed income securities, whereby we interact the cash flows shocks with an indicator variable if the bond is a U.S. Treasury bond. Table 11 summarizes the results. Focusing on Columns (4)-(6), negative cash flow shocks are associated with sales of fixed income securities, but the interaction terms with U.S. Treasuries are statistically insignificant. Thus, pension funds draw on their fixed income portfolios when faced with negative cash flow shocks, but they are not more likely to sell U.S. Treasuries than other fixed income securities.

7 Conclusion

Pension funds increasingly face negative net operating cash flows as benefit payments exceed contributions. Even though negative cash flows make pension funds predictable net sellers, we show that pension funds implement target allocations that are independent of operating cash flows and hold limited safe asset buffers. Funds absorb predictable outflows through pro-rata sales tilted towards fixed income and equities, while negative cash flow shocks mainly lead to equity sales. Within equities, pension funds do not distinguish between more and less liquid stocks and absorb

negative cash flow shocks through pro-rata selling.

Our findings have three broader implications. First, although pension funds are long-term investors with predictable liabilities, they actively demand liquidity in financial markets. The negative cash flows limit the ability of pension funds to act as stabilizers in market downturns. Second, pension fund liquidity needs can generate spillovers to other investors. External asset managers sell assets to meet the cash flow needs of their pension clients, which could affect other institutional investors that hold stakes in the same commingled vehicles. Finally, while establishing retirement systems can foster capital market development (Scharfstein, 2018), when pension funds enter the decumulation phase, their cash outflows can introduce fragility in capital markets.

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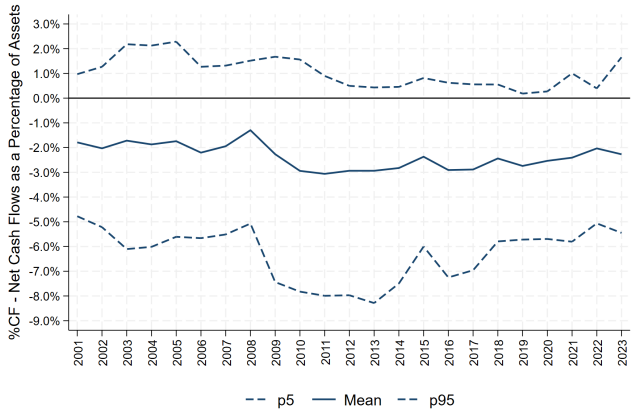
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Figure 1: Pension Fund Cash Flows

Panel A presents the net operating cash flows of U.S. public pension funds over time. *%CF* is measured as the difference between the inflows from contribution payments and the outflows for pension benefit payments and administrative expenditures. Panel B shows the detrended residual cash flows calculated in two stages. First, using robust regressions, we regress the contributions and benefits of each pension fund separately on an annual trend variable to obtain the residual contributions and residual benefits. Second, we estimate the detrended net cash flows as the difference between the residual contributions and benefits. Panel C presents detrended contributions as a percentage of pension assets. Panel D presents the detrended benefits and administrative expenditures as a percentage of pension assets.

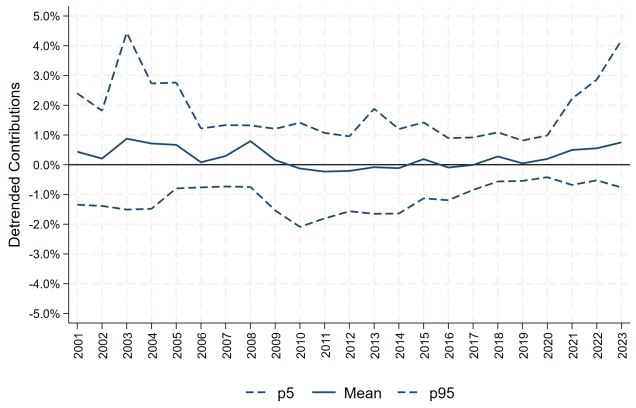
Panel A: Net Operating Cash Flows



Panel B: Detrended Residual Cash Flows



Panel C: Detrended Contributions



Panel D: Detrended Benefits

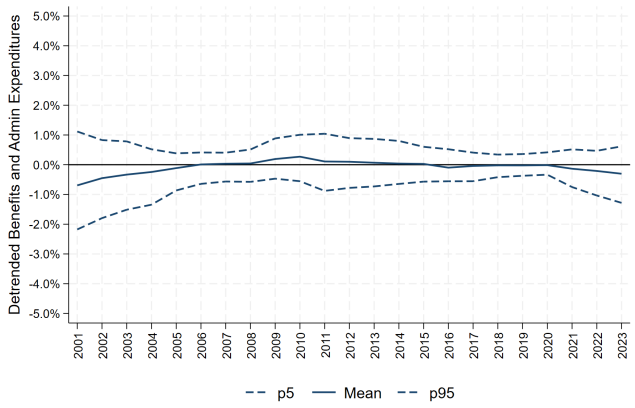


Figure 2: Pension Fund Holdings Data Coverage

This figure shows the total number of pension funds (left y-axis) and the total assets separated into major asset classes (right y-axis) covered in the holdings data sample over time. We distinguish the following asset classes: cash, fixed income, equity, alternatives, and other. Mutual funds are allocated to either equity, fixed income, or other.

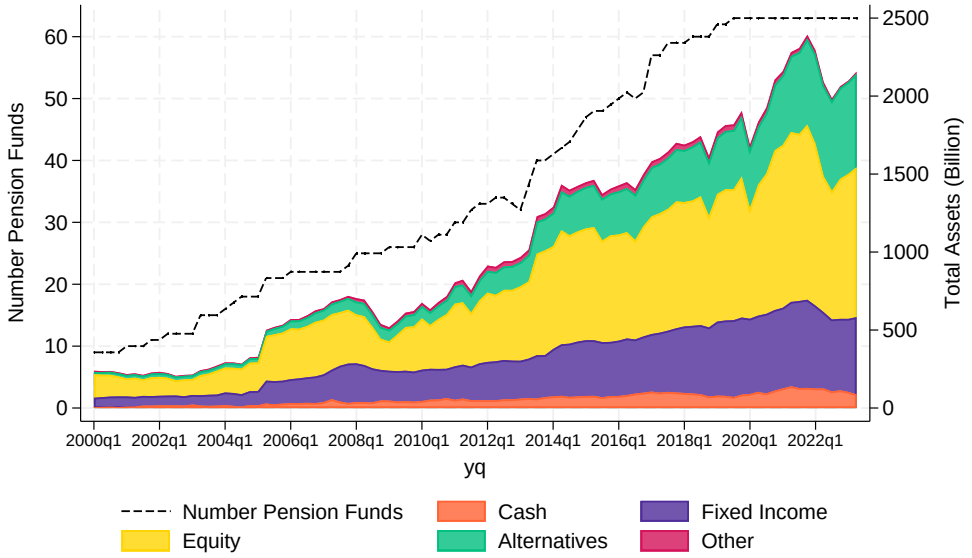


Figure 3: Pension Fund Holdings Data Detailed Asset Allocation

This figure shows the cross-sectional average asset allocation of pension funds over time. We report allocations to cash, US Treasuries, corporate bonds, mortgage-backed securities (MBS), other fixed income, domestic equity, foreign equity, alternatives, and other. Domestic and foreign equity encompass both direct equity investments and equity mutual fund investments. Other fixed income includes, among others, foreign government debt, bank loans, municipality bonds, and fixed income mutual fund investments. Alternatives include private equity, real estate, hedge funds, and infrastructure. Source: public records.

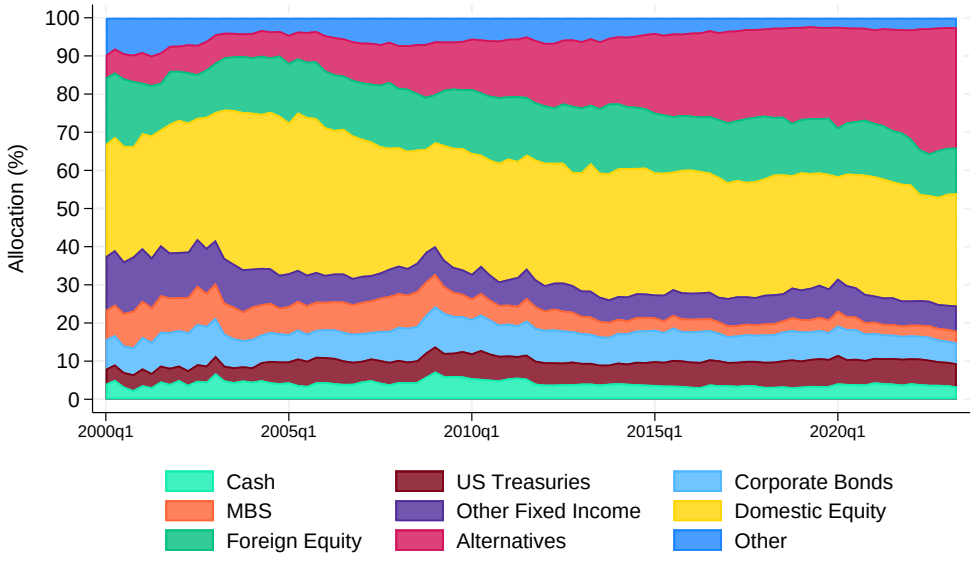
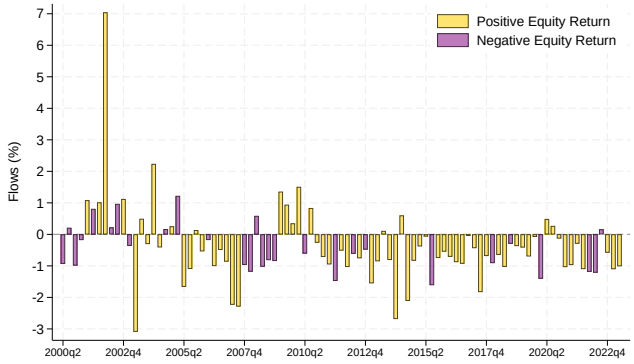


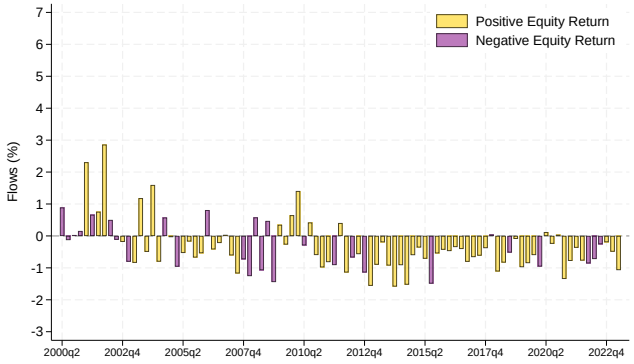
Figure 4: Equity Flows and Equity Returns

This figure shows the flows into equities during periods of positive and negative equity (S&P500) returns. In Panels A and B, flows into equities for pension fund i are computed as $Flow_{i,t} = \sum_{j=1}^{J} \frac{A_{i,j,t} - A_{i,j,t-1} \times (1+R_{j,t})}{TA_{i,t-1}}$, where $A_{i,j,t}$ is the dollar amount invested by pension fund i in stock j in quarter t, $R_{j,t}$ is the return of stock j in that quarter, and $TA_{i,t-1}$ is the total amount of pension fund assets under management at the end of the previous quarter. We report the quarterly flows for the aggregate across all pension funds (Panel A) and for the average pension fund (Panel B) in the public records sample. Panels C and D show the annual equity flows for the full sample of pension funds. In the annual specification, $A_{i,j,t}$ is the dollar amount invested by pension fund i in equity j in year t, and $R^{BM}_{j,t}$ is the median return of pension funds that operate with the same fiscal-year-end in equity j in year t. Since pension funds have different fiscal-year-ends, they do not experience identical equity market returns at reporting dates. Therefore, we shade the bars based on the percentage of pension funds experiencing negative equity returns. We report the annual flows also for the aggregate across all pension funds (value-weighted average, Panel C) and for the average pension fund (Panel D) in our sample. For the value-weighted averages, we use the beginning-of-year total assets as weights.

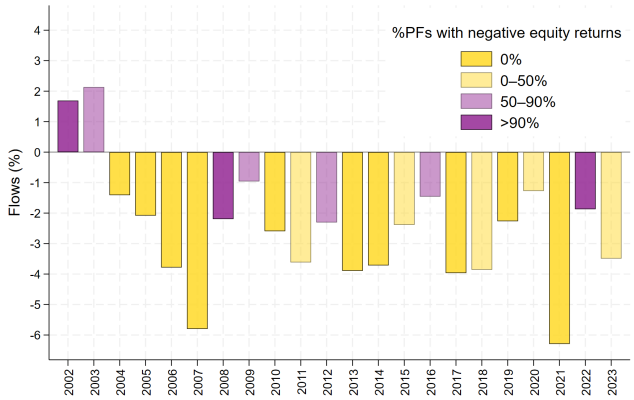
Panel A: Total Public Records Pension Funds



Panel B: Average Public Records Pension Fund



Panel C: Total All Pension Funds



Panel D: Average All Pension Fund

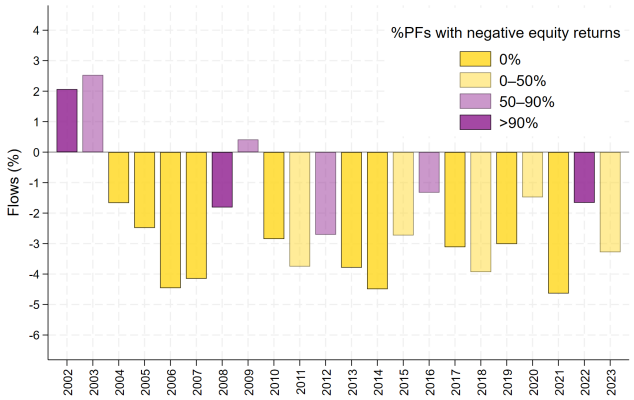
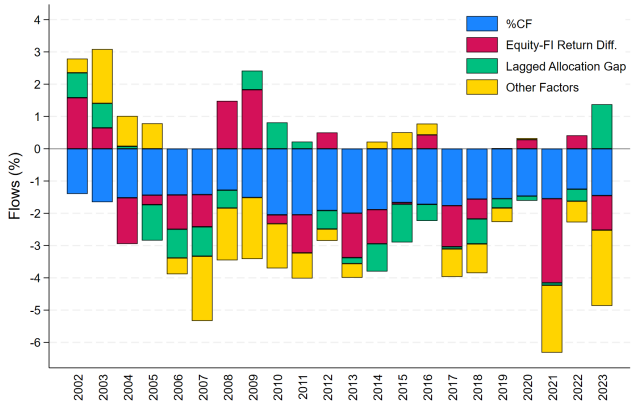


Figure 5: Decomposition of Annual Equity Investment Flows

This figure decomposes the annual equity investment flows of pension funds into four components. We multiply the estimated coefficients from Online Appendix Table D.6 by the realized values of the corresponding explanatory variables at the pension-fund-year level and then aggregate or average the predicted contributions across pension funds. The four components are: (i) the return difference ($R^{BM}_{EQ,t} - R^{BM}_{FI,t}$), capturing rebalancing in response to relative price movements across equity and fixed income; (ii) the allocation gap ($\omega^{Target}_{t-1} - \omega^{Actual}_{t-1}$), capturing active rebalancing toward target allocation weights; (iii) total cash flows (%CF Fit + %CF Residual), capturing liquidity-driven equity sales; and (iv) other factors, which include the contributions of the remaining controls and the residual component. The benchmark return $R^{BM}_{j,t}$ is the median return among pension funds with the same fiscal-year-end for asset class j in year t. Panel A reports the results for the aggregate across pension funds (value-weighted average) and Panel B for the average pension fund.

Panel A: Total All Pension Funds



Panel B: Average All Pension Fund

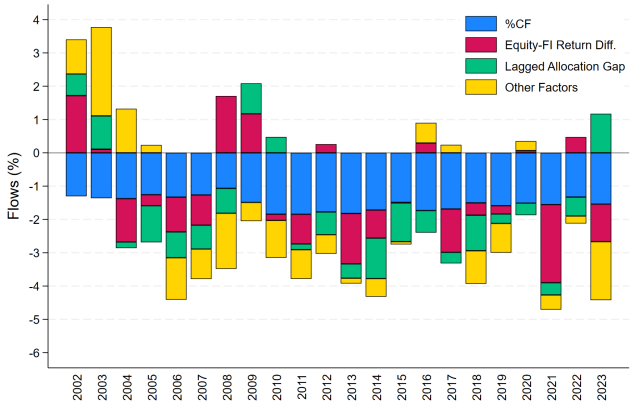


Table 1: Pension Fund Summary Statistics

This table presents summary statistics on pension fund cash flows, characteristics, and target asset allocations. We present statistics for the full sample of pension funds, and for the public records subsample of pension funds that disclose holdings data.

	Full Sample				Public Records Subsample			
	N	Mean	Median	SD	N	Mean	Median	SD
Panel A: Cash Flows								
%Contributions	4,083	5.6	4.9	4.0	867	5.7	5.0	3.6
%Contributions Fit	4,083	5.4	4.8	2.9	867	5.4	5.0	2.7
%Contributions Residuals	4,083	0.3	0.0	2.7	867	0.3	-0.0	2.1
%Benefits	4,083	-8.0	-7.2	3.4	867	-8.0	-7.1	3.5
%Benefits Fit	4,083	-7.9	-7.2	3.4	867	-7.9	-7.1	3.4
%Benefits Residuals	4,083	-0.1	0.0	0.8	867	-0.1	0.0	0.9
%CF	4,083	-2.4	-2.3	3.3	867	-2.3	-2.1	2.8
%CF Fit	4,083	-2.5	-2.4	2.2	867	-2.5	-2.1	2.1
%CF Residuals	4,083	0.2	-0.0	2.8	867	0.2	-0.0	2.2
%CF Predicted	2,222	-2.8	-2.5	2.6	670	-2.7	-2.2	2.5
%CF Shock	2,222	0.1	-0.0	1.8	670	0.2	-0.0	1.8
Panel B: Pension Fund Characteristics								
Pension Fund AUM ($ bil)	4,083	18.3	5.0	36.5	867	28.7	9.9	53.9
GASB Funding Status	4,035	78.0	78.3	16.8	866	76.3	76.4	15.6
Return	4,083	6.5	8.1	10.9	867	7.3	8.0	10.5
Panel C: Target Asset Allocation								
%Cash & FI	3,496	25.9	25.6	7.1	829	24.7	25.0	7.0
%Cash	3,496	0.3	0.0	2.4	829	0.5	0.0	1.7
%Fixed Income	3,496	25.6	25.0	7.4	829	24.2	24.5	7.0
%Risky	3,496	74.1	74.3	7.1	829	75.3	75.0	7.0
%Equity	3,496	50.5	51.0	10.6	829	48.5	48.0	10.8
%Alternatives	3,496	23.6	23.4	13.1	829	26.8	27.0	13.0
%Private Equity	3,496	6.9	7.0	6.0	829	7.8	8.0	6.3
%Real Assets	3,496	9.9	10.0	6.1	829	10.5	10.5	5.7
%Hedge Funds	3,496	4.9	0.0	6.7	829	6.5	5.0	7.5
%Other Alternatives	3,496	1.8	0.0	5.3	829	2.0	0.0	5.8

Table 2: Summary Statistics Holdings Data

In this table, we summarize the number of positions, the number of unique securities, and the allocation to each asset class reported in the public records holdings data. We average in both panels across pension funds and quarters. We report the mean, median, and standard deviation. Other fixed income includes, among others, foreign government debt, bank loans, municipality bonds, and fixed income mutual fund investments. Other alternatives encompasses infrastructure, natural resources, and hedge funds.

	Positions			**Unique Securities**			**Allocation (%)**		
	Mean	Median	SD	Mean	Median	SD	Mean	Median	SD
Cash	149	47	361	26	11	50	4.1	2.8	4.1
Fixed Income									
Corporate Bonds	1102	664	1220	952	646	1019	7.5	7.0	4.9
US Treasuries	144	60	186	105	52	132	6.2	4.4	6.8
MBS	691	275	1088	652	257	1035	4.4	3.9	3.7
Agencies + Foreign Gov Bonds	60	20	111	46	17	77	1.4	0.6	2.1
Other Fixed Income	138	55	217	118	52	168	7.4	6.0	6.8
Equity									
Equity Domestic	2270	1213	3009	1431	962	1461	31.4	31.6	13.8
Equity Foreign	1501	614	2458	935	485	1280	14.7	15.5	10.0
Alternatives									
Private Equity	81	26	119	76	22	111	10.2	7.7	10.3
Real Estate	149	53	257	89	41	117	5.3	5.6	3.8
Other	30	6	70	23	4	54	4.6	0.6	6.9

Table 3: Summary Statistics Derivatives Data

In this table, we summarize the derivatives data by category: linear derivatives (futures/forwards/swaps) and non-linear derivatives (options). We also split linear derivative contracts into equity, fixed income, currency, and other linear derivatives. The first column reports the fraction of pension fund-quarter observations that uses derivatives in each category. The remaining columns report the number of contracts, the total gross notional amount held (in billion USD), and the total gross notional amount as a fraction of total assets. We report the mean, median, and standard deviation. For all derivative categories, the sample contains 47 of the 65 pension funds. We exclude 18 pension funds for which USD notionals cannot be measured consistently.

	Usage (%)	**Contracts (#)**			**Gross Notional ($)**			**Gross Notional (%)**		
		Mean	Median	SD	Mean	Median	SD	Mean	Median	SD
Linear derivatives	69.9	59	16	117	0.6	0.0	1.8	2.0	0.1	3.7
Equity	44.6	8	0	15	0.0	0.0	0.3	0.1	0.0	0.6
Fixed Income	62.0	42	7	96	0.5	0.0	1.7	1.5	0.0	2.8
Currency	43.1	5	0	29	0.0	0.0	0.1	0.4	0.0	1.6
Other	20.9	5	0	28	0.0	0.0	0.0	0.1	0.0	0.3
Non-linear derivatives	60.4	18	3	32	0.2	0.0	1.6	0.3	0.0	1.3

Table 4: Target Asset Allocation and Cash Flows

In this table, observations are at the pension-fund-year level. The dependent variables measure the target asset allocation weights ($\omega_{i,t}$) of pension fund i in year t to cash & fixed income, equity, or alternatives. *%CF* is the ratio of net cash flows to pension fund assets at the beginning of the year. *%CF Fit* is the difference between fitted contributions and benefits scaled by pension assets. *%CF Predicted* is the difference between the predicted contributions and benefits scaled by pension assets. *%CF Volatility* is the volatility of *%CF* over the previous 10 years. We control for the lagged log of pension fund size and the lagged GASB funding ratio. The specifications include pension fund and reporting-year fixed effects. We cluster standard errors by pension fund, and report standard errors in brackets. $^{*}p < .10$; $^{**}p < .05$; $^{***}p < .01$.

	Cash & FI		**Equity**		**Alternatives**	
	(1)	(2)	(3)	(4)	(5)	(6)
Mean Dep. Var.	0.258	0.258	0.503	0.503	0.239	0.239
Panel A: Net Cash Flows						
%CF	0.020	-0.086	-0.153	0.038	0.133	0.048
	[0.078]	[0.053]	[0.113]	[0.041]	[0.135]	[0.053]
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Pension Fund FE		Yes		Yes		Yes
Reporting-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3,342	3,342	3,342	3,342	3,342	3,342
R-squared	0.141	0.579	0.207	0.732	0.305	0.765
Panel B: Fitted Cash Flows						
%CF Fit	0.114	-0.188	-0.392	-0.317	0.279	0.505
	[0.166]	[0.347]	[0.250]	[0.412]	[0.298]	[0.462]
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Pension Fund FE		Yes		Yes		Yes
Reporting-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3,342	3,342	3,342	3,342	3,342	3,342
R-squared	0.142	0.578	0.210	0.732	0.306	0.766
Panel C: Predicted Cash Flows						
%CF Predicted	0.003	-0.004	-0.112	-0.071	0.110	0.075
	[0.166]	[0.149]	[0.213]	[0.216]	[0.279]	[0.293]
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Pension Fund FE		Yes		Yes		Yes
Reporting-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,116	2,114	2,116	2,114	2,116	2,114
R-squared	0.046	0.734	0.023	0.809	0.038	0.803
Panel D: Volatility of Net Cash Flows						
%CF Volatility	-0.165**	0.000	0.117	0.278	0.048	-0.277
	[0.081]	[0.095]	[0.126]	[0.299]	[0.146]	[0.281]
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Pension Fund FE		Yes		Yes		Yes
Reporting-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,116	2,114	2,116	2,114	2,116	2,114
R-squared	0.049	0.734	0.023	0.811	0.038	0.804

Table 5: Asset Allocation to Cash and U.S. Treasuries and Cash Flows

In this table, observations are at the pension fund-year level. The dependent variable equals the actual allocation to cash and U.S. Treasury securities based on the holdings data obtained through public records requests. Cash includes T-bills, money market funds, and bank deposits. *%CF* is the ratio of net cash flows to pension fund assets at the beginning of the year. *%CF Fit* is the difference between fitted contributions and benefits scaled by pension assets. *%CF Predicted* is the difference between the predicted contributions and benefits scaled by pension assets. *%CF Volatility* is the volatility of *%CF* over the previous 10 years. We control for the lagged log of pension fund size and the lagged GASB funding ratio. The specifications include reporting-year fixed effects. We cluster standard errors by pension fund, and report standard errors in brackets. $^{*}p < .05$; $^{**}p < .01$; $^{***}p < .001$.

	(1)	(2)	(3)	(4)
Mean Dep. Var.	0.103	0.103	0.101	0.101
%CF	-0.353			
	[0.254]			
%CF Fit		-0.804		
		[0.442]		
%CF Predicted			-0.562	
			[0.337]	
%CF Volatility				-0.048
				[0.204]
Controls	Yes	Yes	Yes	Yes
Reporting-Year FE	Yes	Yes	Yes	Yes
Observations	840	840	652	652
R-squared	0.179	0.204	0.176	0.148

Table 6: Asset Class Investment Flows and Cash Flows

In this table, observations are at the pension-fund-year level. The dependent variables measure the investment flow of pension fund i in year t into cash & fixed income, equity, or alternatives. *%CF Fit* is the difference between fitted contributions and benefits scaled by pension assets at the beginning of the year. *%CF Residual* is the difference between residual contributions and residual benefits scaled by pension assets. Using piecewise decomposition, we split *%CF Residual* into %CF Residual $\text{Pos}_{i,t} = max(\%\text{CF Residual}_{i,t}, 0)$ and %CF Residual $\text{Neg}_{i,t} = min(\%\text{CF Residual}_{i,t}, 0)$. The reported p-value tests the null that the coefficients on the positive and negative components are equal. We control for the lagged log of pension fund size, lagged GASB funding ratio, and lagged allocation gap. The allocation gap captures the difference between the actual and target asset allocation ($\omega_{i,j,t-1}^{Target} - \omega_{i,j,t-1}^{Actual}$) of pension fund i in asset class j in year $t-1$. The specifications include pension fund and reporting-year fixed effects. We cluster standard errors by pension fund, and report standard errors in brackets. $^{*}p < .10$; $^{**}p < .05$; $^{***}p < .01$.

	Cash & FI		**Equity**		**Alternatives**	
	(1)	(2)	(3)	(4)	(5)	(6)
Mean Dep. Var.	-0.005	-0.005	-0.026	-0.026	0.003	0.003
%CF Fit	0.345***	0.418***	0.542***	0.505***	0.143	0.111
	[0.102]	[0.098]	[0.112]	[0.100]	[0.098]	[0.092]
%CF Residuals	0.689***		0.264**		0.077**	
	[0.129]		[0.106]		[0.035]	
%CF Residuals Pos		0.782***		0.215**		0.036*
		[0.112]		[0.107]		[0.019]
%CF Residuals Neg		-0.074		0.673***		0.415**
		[0.107]		[0.141]		[0.173]
Allocation Gap	0.372***	0.378***	0.365***	0.367***	0.273***	0.274***
	[0.048]	[0.049]	[0.042]	[0.042]	[0.025]	[0.025]
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Pension Fund FE	Yes	Yes	Yes	Yes	Yes	Yes
Reporting-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3,230	3,230	3,230	3,230	3,217	3,217
R-squared	0.437	0.451	0.337	0.341	0.235	0.239
p-value test		0.00		0.04		0.03

Table 7: Investment Income from Assets and Cash Flows

In this table, observations are at the pension fund-year level. The dependent variable equals the total investment income (dividends and coupons), relative to total equity and fixed income assets, based on the holdings data obtained through public records requests. *%CF* is the ratio of net cash flows to pension fund assets at the beginning of the year. *%CF Fit* is the difference between fitted contributions and benefits scaled by pension assets. *%CF Predicted* is the difference between the predicted contributions and benefits scaled by pension assets. *%CF Volatility* is the volatility of *%CF* over the previous 10 years. We control for the lagged log of pension fund size and the lagged GASB funding ratio. The specifications include reporting-year fixed effects. We cluster standard errors by pension fund, and report standard errors in brackets. $^{*}p < .05$; $^{**}p < .01$; $^{***}p < .001$.

	(1)	(2)	(3)	(4)
Mean Dep. Var.	2.573	2.573	2.470	2.470
%CF	0.025			
	[0.024]			
%CF Fit		0.034		
		[0.036]		
%CF Predicted			0.039	
			[0.026]	
%CF Volatility				0.026
				[0.037]
Controls	Yes	Yes	Yes	Yes
Reporting-Year FE	Yes	Yes	Yes	Yes
Observations	804	804	645	645
R-squared	0.213	0.214	0.148	0.138

Table 8: Asset Class Investment Flows and Cash Flows Conditional on Returns

In this table, observations are at the pension-fund-year level. Panel A studies the subsample of observations in periods when equity returns are higher than fixed income returns. Panel B reports results for periods when equity returns are lower than fixed income returns. The dependent variables measure the investment flow of pension fund i in year t into cash & fixed income, equity, or alternatives. *%CF Fit* is the difference between fitted contributions and benefits scaled by pension assets at the beginning of the year. *%CF Residual* is the difference between residual contributions and residual benefits scaled by pension assets. Using piecewise decomposition, we split *%CF Residual* into %CF Residual $\text{Pos}_{i,t} = max(\%\text{CF Residual}_{i,t}, 0)$ and %CF Residual $\text{Neg}_{i,t} = min(\%\text{CF Residual}_{i,t}, 0)$. We control for the lagged log of pension fund size, lagged GASB funding ratio, and lagged allocation gap. The allocation gap captures the difference between the actual and target asset allocation ($\omega^{Target}_{i,j,t-1} - \omega^{Actual}_{i,j,t-1}$) of pension fund i in asset class j in year $t-1$. The specifications include pension fund and reporting-year fixed effects. We cluster standard errors by pension fund, and report standard errors in brackets. $^*p < .10$; $^{**}p < .05$; $^{***}p < .01$.

	Cash & FI		**Equity**		**Alternatives**	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Subsample of Time Periods when $R^{BM}_{EQ,t} > R^{BM}_{FI,t}$						
Mean Dep. Var.	0.003	0.003	-0.034	-0.034	0.004	0.004
%CF Fit	0.362***	0.417***	0.505***	0.494***	0.203	0.170
	[0.105]	[0.113]	[0.134]	[0.134]	[0.125]	[0.116]
%CF Residuals	0.398***		0.521***		0.116**	
	[0.063]		[0.049]		[0.053]	
%CF Residuals Pos		0.497***		0.500***		0.057
		[0.067]		[0.069]		[0.035]
%CF Residuals Neg		-0.063		0.617***		0.389*
		[0.117]		[0.153]		[0.226]
Allocation Gap	0.371***	0.376***	0.390***	0.390***	0.264***	0.267***
	[0.062]	[0.062]	[0.052]	[0.052]	[0.028]	[0.029]
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Pension Fund FE	Yes	Yes	Yes	Yes	Yes	Yes
Reporting-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,000	2,000	2,000	2,000	1,991	1,991
R-squared	0.346	0.354	0.356	0.356	0.262	0.264
Panel B: Subsample of Time Periods when $R^{BM}_{EQ,t} < R^{BM}_{FI,t}$						
Mean Dep. Var.	-0.019	-0.019	-0.013	-0.013	0.001	0.001
%CF Fit	0.490***	0.502***	0.422***	0.413***	-0.029	-0.034
	[0.143]	[0.142]	[0.129]	[0.130]	[0.138]	[0.136]
%CF Residuals	0.902***		0.072		0.030	
	[0.064]		[0.054]		[0.024]	
%CF Residuals Pos		0.944***		0.042		0.013
		[0.034]		[0.034]		[0.018]
%CF Residuals Neg		0.103		0.629***		0.364**
		[0.188]		[0.134]		[0.184]
Allocation Gap	0.353***	0.355***	0.287***	0.291***	0.263***	0.261***
	[0.041]	[0.040]	[0.048]	[0.048]	[0.040]	[0.039]
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Pension Fund FE	Yes	Yes	Yes	Yes	Yes	Yes
Reporting-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,229	1,229	1,229	1,229	1,225	1,225
R-squared	0.619	0.627	0.426	0.432	0.307	0.310

Table 9: Investment Flows and Cash Flows by Alternatives Tertiles

In this table, observations are at the pension-fund-year level. The dependent variable measures the investment flow of pension fund i in year t into cash & fixed income and equity. We split pension funds into tertiles by lagged actual allocation to alternatives, or lagged actual allocation to risky assets, which includes both equity and alternatives. We report results for the high and low tertiles. *%CF Fit* is the difference between fitted contributions and benefits scaled by pension assets at the beginning of the year. *%CF Residual* is the difference between residual contributions and residual benefits scaled by pension assets. Using piecewise decomposition, we split *%CF Residual* into %CF Residual $\text{Pos}_{i,t} = max(\%\text{CF Residual}_{i,t}, 0)$ and %CF Residual $\text{Neg}_{i,t} = min(\%\text{CF Residual}_{i,t}, 0)$. The reported p-value tests the null that the coefficients on the positive and negative components are equal. We control for the lagged log of pension fund size, lagged GASB funding ratio, and lagged allocation gap. The specifications include pension fund and reporting-year fixed effects. We cluster standard errors by pension fund, and report standard errors in brackets. $^*p < .10$; $^{**}p < .05$; $^{***}p < .01$.

	%Alternatives Tertiles				**%Risky Tertiles**			
	Low		**High**		**Low**		**High**	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Equity Investment Flows								
Mean Dep. Var.	-0.020	-0.020	-0.025	-0.025	-0.012	-0.012	-0.035	-0.035
%CF Fit	0.308	0.295	0.831***	0.661**	0.930**	0.930**	0.569***	0.568***
	[0.306]	[0.311]	[0.300]	[0.288]	[0.358]	[0.359]	[0.195]	[0.212]
%CF Residuals	0.360***		0.202***		0.354***		0.504***	
	[0.082]		[0.067]		[0.109]		[0.059]	
%CF Residuals Pos		0.386***		0.166**		0.359***		0.503***
		[0.088]		[0.066]		[0.120]		[0.081]
%CF Residuals Neg		0.193		0.514***		0.326		0.507**
		[0.232]		[0.109]		[0.383]		[0.219]
Allocation Gap	0.439***	0.438***	0.459***	0.455***	0.439***	0.439***	0.381***	0.381***
	[0.092]	[0.092]	[0.070]	[0.071]	[0.082]	[0.082]	[0.055]	[0.055]
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pension Fund FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Reporting-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	961	961	1,128	1,128	981	981	1,099	1,099
R-squared	0.495	0.496	0.327	0.329	0.463	0.463	0.399	0.399
p-value test		0.44		0.01		0.94		0.99
Panel B: Cash and Fixed Income Investment Flows								
Mean Dep. Var.	-0.014	-0.014	0.000	0.000	-0.021	-0.021	0.006	0.006
%CF Fit	0.249	0.251	-0.141	0.373	-0.031	-0.031	0.082	0.192
	[0.180]	[0.180]	[0.346]	[0.338]	[0.316]	[0.307]	[0.169]	[0.170]
%CF Residuals	0.636***		0.744***		0.645***		0.277**	
	[0.079]		[0.106]		[0.092]		[0.107]	
%CF Residuals Pos		0.633***		0.852***		0.683***		0.441***
		[0.091]		[0.084]		[0.089]		[0.116]
%CF Residuals Neg		0.657**		-0.198**		0.425		-0.206**
		[0.260]		[0.078]		[0.368]		[0.082]
Allocation Gap	0.481***	0.481***	0.373***	0.377***	0.456***	0.456***	0.262***	0.267***
	[0.095]	[0.095]	[0.074]	[0.075]	[0.081]	[0.081]	[0.061]	[0.061]
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pension Fund FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Reporting-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	961	961	1,128	1,128	981	981	1,099	1,099
R-squared	0.535	0.535	0.512	0.534	0.532	0.533	0.359	0.372
p-value test		0.94		0.00		0.51		0.00

Table 10: Equity Security Flows and Cash Flows

In this table, observations are at the pension-fund-security-year level. The dependent variable measures the investment flow (in basis points) of pension fund i in stock j in reporting year t, defined as $Flow_{i,j,t} = \sum_{q=1}^{4} \frac{A_{i,j,tq} - A_{i,j,tq-1} \times (1+R_{j,tq})}{TA_{i,tq-1}}$, where the four quarters end at pension fund i's reporting date, $A_{i,j,tq}$ is the dollar amount of assets invested by pension fund i in stock j in quarter q, $R_{j,tq}$ is the return of stock j in that quarter, and $TA_{i,tq-1}$ is the total amount of pension fund assets under management at the end of the previous quarter. We interact the cash flows with measures of stock liquidity: the Amihud measure and market cap (MVE). Amihud High are stocks in the top tercile of the Amihud measure, i.e. the least liquid stocks. MVE Low are stocks in the bottom tercile of total market cap. The specifications include fixed effects as reported. We cluster standard errors by fund and security, and report standard errors in brackets. $^{*}p < .05$; $^{**}p < .01$; $^{***}p < .001$.

Panel A: Amihud Measure	(1)	(2)	(3)	(4)	(5)	(6)
Mean Dep. Var.	0.102	0.097	0.097	0.102	0.097	0.097
%CF Residuals	0.014	0.015				
	[0.010]	[0.009]				
%CF Residuals Pos				0.018	0.020*	
				[0.010]	[0.008]	
%CF Residuals Neg				-0.023	-0.060	
				[0.053]	[0.071]	
%CF Residuals × Amihud High	-0.009	-0.009	-0.005			
	[0.009]	[0.008]	[0.007]			
%CF Residuals Pos × Amihud High				-0.012	-0.014	-0.007
				[0.010]	[0.008]	[0.007]
%CF Residuals Neg × Amihud High				0.027	0.060	0.018
				[0.048]	[0.058]	[0.025]
Amihud High	-0.034			-0.023		
	[0.022]			[0.024]		
Reporting-Year FE	Yes			Yes		
Pension Fund FE	Yes	Yes		Yes	Yes	
Security-Reporting-Year FE		Yes	Yes		Yes	Yes
Pension-Reporting-Year FE			Yes			Yes
Observations	1,451,516	1,160,379	1,160,379	1,451,516	1,160,379	1,160,379
R-squared	0.021	0.273	0.300	0.021	0.273	0.300
Panel B: Market Value Equity (MVE)	(1)	(2)	(3)	(4)	(5)	(6)
Mean Dep. Var.	0.102	0.097	0.097	0.102	0.097	0.097
%CF Residuals	0.015	0.015				
	[0.010]	[0.009]				
%CF Residuals Pos				0.018	0.021*	
				[0.011]	[0.008]	
%CF Residuals Neg				-0.022	-0.065	
				[0.055]	[0.072]	
%CF Residuals × MVE Low	-0.010	-0.011	-0.008			
	[0.010]	[0.009]	[0.008]			
%CF Residuals Pos × MVE Low				-0.013	-0.017	-0.010
				[0.011]	[0.009]	[0.008]
%CF Residuals Neg × MVE Low				0.022	0.077	0.026
				[0.052]	[0.060]	[0.023]
MVE Low	-0.036			-0.027		
	[0.022]			[0.022]		
Reporting-Year FE	Yes			Yes		
Pension Fund FE	Yes	Yes		Yes	Yes	
Security-Reporting-Year FE		Yes	Yes		Yes	Yes
Pension-Reporting-Year FE			Yes			Yes
Observations	1,460,000	1,165,755	1,165,755	1,460,000	1,165,755	1,165,755
R-squared	0.022	0.273	0.300	0.022	0.273	0.300

Table 11: Fixed Income Security Flows and Cash Flows

In this table, observations are at the pension-fund-security-reporting-year level. The dependent variable measures the investment flow (in basis points) of pension fund i in bond j in reporting year t, defined as $Flow_{i,j,t} = \sum_{q=1}^{4} \frac{A_{i,j,tq} - A_{i,j,tq-1} \times (1+R_{j,tq})}{TA_{i,tq-1}}$, where the four quarters end at pension fund i's reporting date, $A_{i,j,tq}$ is the dollar amount of assets invested by pension fund i in bond j in quarter q, $R_{j,tq}$ is the return of bond j in that quarter, and $TA_{i,tq-1}$ is the total amount of pension fund assets under management at the end of the previous quarter. We interact the cash flows with an indicator variable whether the bond is a U.S. Treasury security. The specifications include fixed effects as reported. We cluster standard errors by fund and security, and report standard errors in brackets. $^{*}p < .05$; $^{**}p < .01$; $^{***}p < .001$.

	(1)	(2)	(3)	(4)	(5)	(6)
Mean Dep. Var.	-0.018	-0.004	-0.004	-0.018	-0.004	-0.004
%CF Residuals	0.0111***	0.0153***				
	[0.0031]	[0.0039]				
%CF Residuals Pos				0.0084***	0.0128**	
				[0.0023]	[0.0040]	
%CF Residuals Neg				0.0230*	0.0263***	
				[0.0097]	[0.0074]	
%CF Residuals × U.S. Treasuries	0.1021*	0.0704	0.0761			
	[0.0490]	[0.0486]	[0.0442]			
%CF Residuals Pos × U.S. Treasuries				0.0906	0.0421	0.0560
				[0.0528]	[0.0492]	[0.0506]
%CF Residuals Neg × U.S. Treasuries				0.1716	0.2526	0.2039
				[0.1421]	[0.2364]	[0.2005]
U.S. Treasuries	0.0994			0.1205		
	[0.0983]			[0.1079]		
Reporting-Year FE	Yes			Yes		
Pension Fund FE	Yes	Yes		Yes	Yes	
Security-Reporting-Year FE		Yes	Yes		Yes	Yes
Pension-Reporting-Year FE			Yes			Yes
Observations	6,636,739	4,122,553	4,122,549	6,636,739	4,122,553	4,122,549
R-squared	0.003	0.199	0.228	0.003	0.199	0.228

Online Appendix A: Target Date Fund Allocations over the Life Cycle

Target date funds provide a useful benchmark for how a participant's age affects the desired allocation to safe assets as they are based on life cycle models (Viceira, 2001; Cocco et al., 2005).[25] Table A.1 compares target date funds for participants who retire now and in 5, 10, or 15 years. We map these horizons into the standard 2025, 2030, 2035, and 2040 vintages, respectively. Because the funds are designed for retirement at approximately age 65, these vintages correspond roughly to participants ages 65, 60, 55, and 50 in 2025. The comparison shows that age composition is economically important: relative to the age-50 (2040) vintage, the age-65 (2025 or retirement) vintage allocates between 25 and 41 percentage points more to cash and fixed income across the four providers.

This benchmark is also useful for interpreting the variation in age composition in our sample. In the sample, average participant age increases substantially over time. The 25th percentile of average participant age rises from 51.9 years in 2001 to 56.6 years in 2023, while the 75th percentile rises from 56.6 years in 2001 to 59.5 years in 2023. Mapping these sample changes into the TDF glidepath in Table A.1 shows that they are economically meaningful. Across providers, moving from age 50 to 55 is associated with a 7.1 to 15.3 percentage point increase in allocations to cash and fixed income, while moving from age 55 to 60 is associated with a 7.7 to 12.0 percentage point increase. Assuming linear interpolation between adjacent vintages, the increase in the 25th percentile of average participant age from 51.9 to 56.6 years implies a 7.2 to 12.1 percentage point higher target allocation to cash and fixed income. Similarly, the increase in the 75th percentile from 56.6 to 59.5 years implies a 4.5 to 7.0 percentage point higher target allocation. The same benchmark is informative for the cross-sectional relation between expected cash flows and age. Pension funds with fitted expected cash flows below the 25th percentile (*%CF Fit* of -3.7%) have an average participant age of 57.4 years, while funds with fitted expected cash flows above the 75th percentile (*%CF Fit* of -1.2%) have an average participant age of 53.8 years. Under the TDF glidepath, this 3.6-year difference in average participant age implies a 5.5 to 8.2 percentage point higher target allocation to cash and fixed income for the funds with more negative expected cash flows.

Table A.1: Cash and Fixed-Income Allocations of Major Target-Date Funds

	Expected time to retirement				
Provider and series	**Now**	**5 years**	**10 years**	**15 years**	**Sources**
Target vintage	**2025**	**2030**	**2035**	**2040**	
Approximate participant age	**65**	**60**	**55**	**50**	
BlackRock LifePath Index	60.0%	41.0%	29.0%	19.0%	prospectus
Vanguard Target Retirement	48.6%	38.5%	30.8%	23.2%	prospectus
Fidelity Freedom Index	48.4%	44.0%	35.9%	20.6%	25/ 30/ 35/ 40
State Street Target Retirement	52.6%	39.8%	29.3%	22.2%	25/ 30/ 35/ 40
Average					

Notes: Entries are the percentage of fund assets allocated to cash, short-term assets, and fixed income. Every link in the final column leads to the official document or provider page containing the underlying allocation figures. BlackRock entries are printed directly in the cited prospectus target allocation table. Vanguard entries are exact sums of the U.S., foreign, and inflation-indexed fixed income components printed in the cited prospectus. Fidelity entries are exact sums of "Bonds" and "Short-Term Debt & Net Other Assets". State Street entries are the provider reported "Fixed Income" allocations printed on the linked official pages; cash-like assets are classified by State Street within its reported allocation categories.

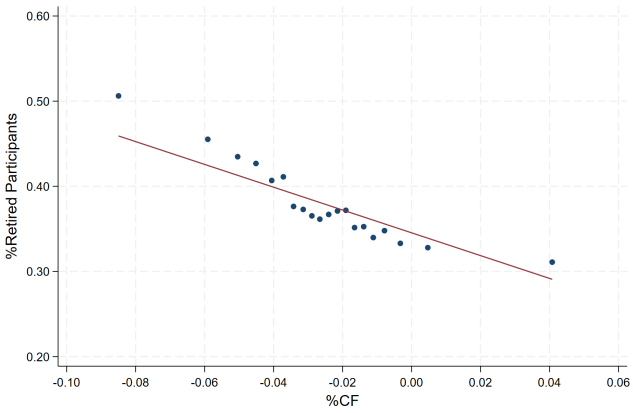
[25] For instance, Vanguard's approach to target date funds explicitly cites the life cycle literature: Vanguard research.

Online Appendix B: Cash Flow Measures

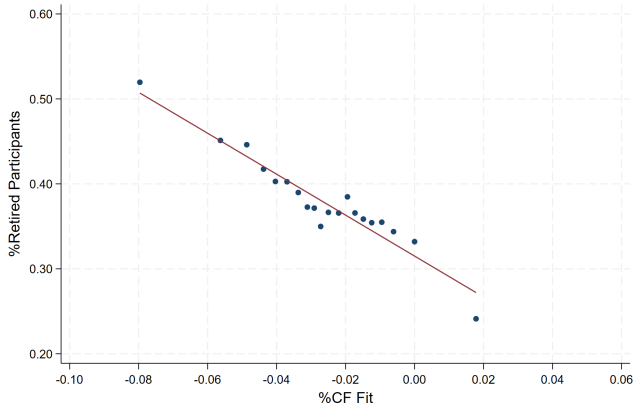
Figure B.1: Pension Fund Cash Flows and the Percentage of Retired Participants

These figures present binned scatterplots of the cash flow measures and the percentage of retired participants, which is the ratio of retired to total pension fund participants.

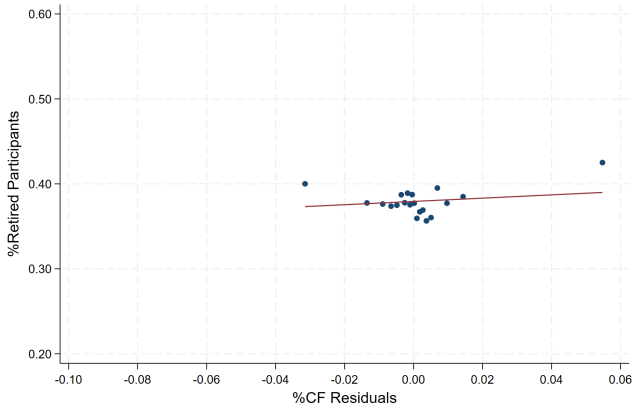
Panel A: Net Operating Cash Flows



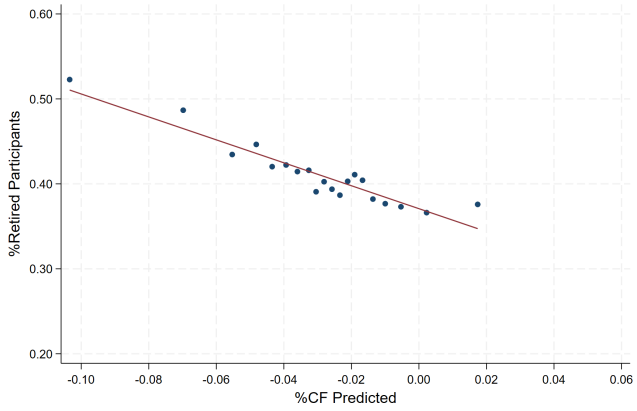
Panel B: Fitted Cash Flows



Panel C: Residual Cash Flows



Panel D: Predicted Cash Flows



Panel E: Cash Flow Shocks

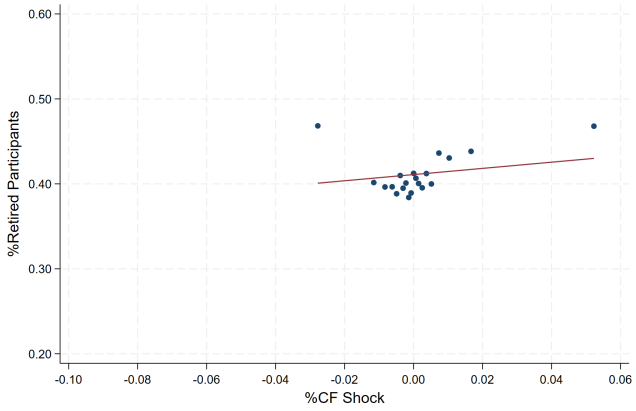


Table B.1: Correlations of Cash Flow Measures

	%CF	%CF Fit	%CF Residuals	%CF Predicted
%CF Fit	0.746			
%CF Residuals	0.596	-0.090		
%CF Predicted	0.774	0.869	0.110	
%CF Shock	0.338	-0.182	0.724	-0.335

Table B.2: Examples of Extreme Residual Cash Flows

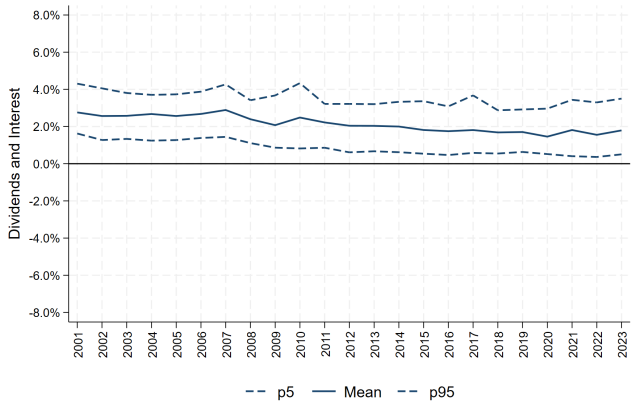
This table presents 10 examples of pension funds experiencing extreme positive and negative residual cash flows. For every case, we list the fiscal year of the event, the assets under management (AUM) in $ bil, %CF, %CF Fit, and %CF Residual. The last column summarizes the main reason for the extreme residual cash flows. Positive residual cash flows are due to high contribution inflows financed either from general reserves and revenue or by issuing a pension obligation bond. Negative residual cash flows can be due to low contribution inflows below the actuarially required contributions (ARC) or high outflows to pay for plan transfers and lump sum withdrawals.

Pension Fund	Year	AUM	%CF	%CF Fit	%CF Residuals	Reason for Extreme %CF Residuals
Panel A: Positive Residual Cash Flows						
San Diego County ERA	2003	4.10	11.9	-2.1	14.0	Contributions - General Reserves and Revenue
Illinois State Universities RS	2004	12.59	10.7	-4.9	15.6	Contributions - Pension Obligation Bond
Illinois Teachers RS	2004	31.54	17.0	-4.1	21.1	Contributions - Pension Obligation Bond
City of Detroit General RS	2005	3.32	20.7	-8.0	28.6	Contributions - Pension Obligation Bond
West Virginia RS	2007	7.96	18.1	-0.9	19.0	Contributions - Tobacco Settlement Proceeds
Chicago Transit Authority ERP	2008	1.74	92.5	-15.4	107.8	Contributions - Pension Obligation Bond
Alaska RMB	2015	13.85	16.9	-4.7	21.6	Contributions - General Reserves and Revenue
Houston Police Officers PS	2018	5.49	12.7	-3.1	15.8	Contributions - Pension Obligation Bond
Arizona Public Safety Personnel RS	2022	16.32	19.6	0.6	19.0	Contributions - General Reserves and Revenue
Indiana Public RS	2023	31.11	10.1	-0.4	10.5	Contributions - General Reserves and Revenue
Panel B: Negative Residual Cash Flows						
Illinois State Board of Investment	2006	10.90	-6.7	-2.4	-4.3	Contributions Below ARC
University of California RS	2008	42.02	-7.3	-2.1	-5.2	High Outflows - Plan Transfers
Kentucky RS	2010	10.28	-8.5	-5.2	-3.3	Contributions Below ARC
Chicago Public School Teachers PRF	2013	9.67	-9.9	-5.8	-4.1	Contributions Below ARC
City of Detroit Police and Fire RS	2013	3.03	-11.5	-8.3	-3.3	Contributions Below ARC
New York City Board of Education RS	2013	2.65	-6.7	0.0	-6.7	High Outflows - Plan Transfers
City of Detroit General RS	2014	2.02	-17.8	-9.6	-8.2	Contributions Below ARC
Chicago Policemen ABF	2016	2.87	-11.1	-3.9	-7.1	Contributions Below ARC
Dallas Police & Fire PS	2016	2.15	-25.9	-3.7	-22.2	Outflows - Withdrawals
Oklahoma Firefighters PRS	2021	3.52	-9.2	-1.8	-7.4	Outflows - Withdrawals

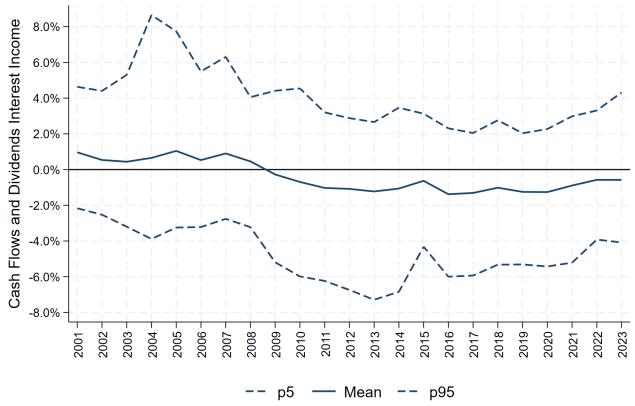
Figure B.2: Pension Fund Cash Flows and Investment Income

Investment income is part of the investment returns. In Panels A and B, the investment income is defined narrowly and includes only income from interest payments and dividends as reported in the PPD data. Panels C and D use a broader definition that defines investment income as income from interest payments, dividends, limited partnerships, and securities lending, net of investment expenses (i.e., all investment return components reported in the PPD dataset, except changes in value of investments). Panels A and C present the investment income as a percentage of assets over time. Panels B and D add the investment income to the net operating cash flows to show total net cash flows from operations and investment activity as a percentage of assets.

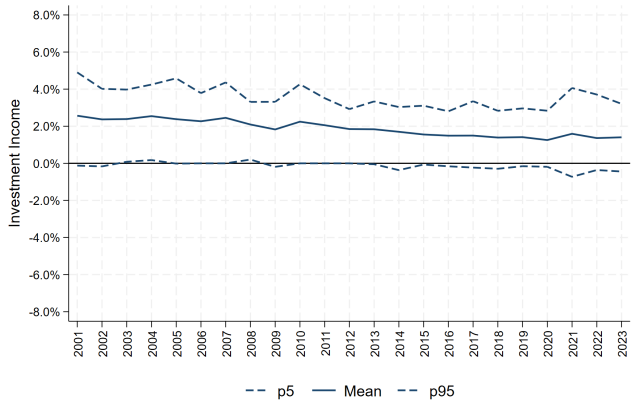
Panel A: Dividends and Interest Income



Panel B: Cash Flows and Div Int Income



Panel C: Investment Income



Panel D: Cash Flows and Investment Income

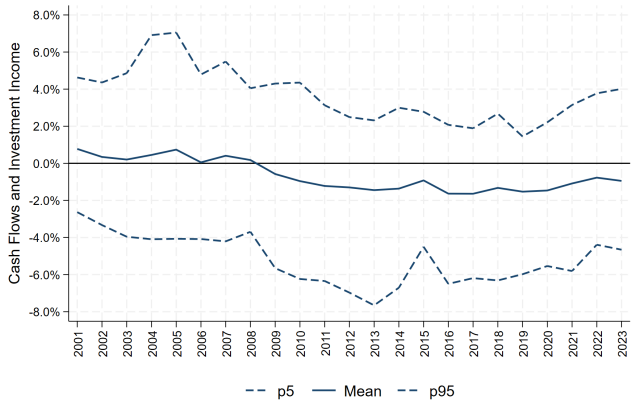
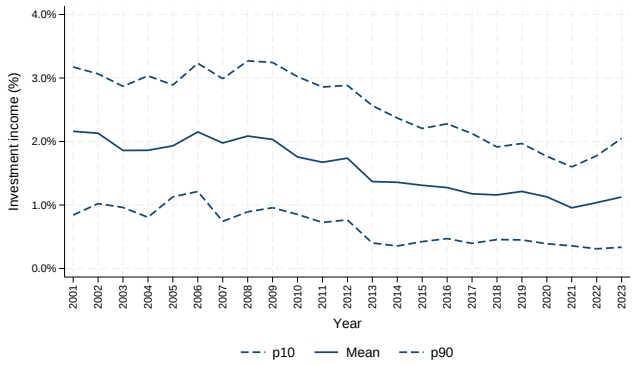


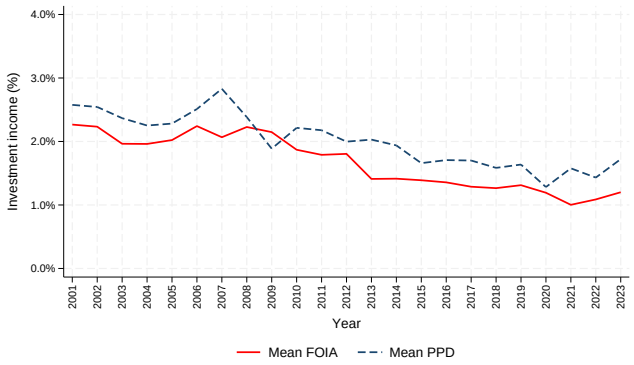
Figure B.3: Investment Income from Holdings Data

We construct a direct measure of investment income by aggregating, at the pension-fund level, all interest (coupon) and dividend payments on individual securities in our public records holdings data (weighted by total position size). Panel A shows the equal-weighted cross-sectional mean and the 10th and 90th percentiles of this direct investment income measure as a percentage of assets over time. Panel B compares the equal-weighted mean of our direct measure with the equal-weighted mean of investment income reported in PPD (interest and dividends only), using the sample of fund-years for which both measures are available.

Panel A: Dividends and Interest Public Records



Panel B: Dividends and Interest Public Records vs PPD



Online Appendix C: Public Records Requests of Pension Fund Holdings

C.1 Public Records Request Process

This appendix outlines the methodology for collecting holdings data from U.S. public pension funds using public disclosure requests under the Freedom of Information Act (FOIA).

In each public disclosure request, we included a formal letter describing the research project and specifying the requested data. We asked for the following information from each pension fund:

1. Quarterly asset holdings from 2000Q1 through 2023Q2, or the earliest available quarter.
2. Coverage across all asset types, including equities, fixed income, derivatives, cash, and private assets.

We note in the request that custodians typically maintain these records and can share them at no cost.

C.1.1 Response Summary and Public Records Subsample Construction

The table below summarizes the outcomes of the public records requests and explains the construction of the public records subsample of pension funds that disclose holdings data.

Public Records Sample Construction	**# Pension Funds**
Total Public Records Requests Submitted	178
No Response or Denied Request	−53
Responses that Require High Fee	−3
Responses that Provide Data	122
Responses without Holdings Data	−14
Data on an Annual instead of Quarterly Frequency	−19
Data Covers Less than 5 Years	−9
Missing Assets Compared to PPD	−15
Final Public Records Sample	65

Our sample contains 186 pension funds, but we could only submit 181 requests to existing pension funds. During our sample period, 5 pension funds were merged, and we could not submit a request to them due to missing contact information. For example, Indiana PERF and Indiana Teachers operated as separate pension funds until 2011. In 2012, the two funds were merged into the newly established Indiana Public Retirement System. We could not submit a separate request to Indiana PERF and Indiana Teachers, but we sent a public records request to the Indiana Public Retirement System. Additionally, for 3 pension funds, we were not able to find the contact information to make the public records requests, so we ended up with a total of 178 submitted requests.

Not all pension funds responded positively to our public records request: 27 pension funds did not respond to our request at all, while 26 pension funds denied our request. In some states, requests were denied because citizenship is required to make the public records requests. In other states, pension funds are allowed to deny our request as the local public records regulations exempt them from sharing holdings data. In addition, pension funds are not required to respond if they do not possess the data and/or collecting the data for the response would create substantial costs for their organizations. For example,

the Ohio Police & Fire Pension Fund denied our request because it was considered "overly broad and unduly burdensome".

Many pension funds delivered the data at no cost, but 14 funds requested that we pay a fee for the data collection and provision. These fee estimates varied widely, ranging from $1.25 for a full request, all the way to $5,000 for one quarter of holdings data. We paid the fee for 11 pension funds, but we did not pay any fees above $2,550 for a total request.

For the median request, we received the first response in one month, and it typically takes an additional three months to receive the holdings data. In many cases, we had to make multiple follow-up requests for missing data or clarifications about the provided data.

C.1.2 Data Verification and Processing

Once data are received, we follow a structured process for verification and cleaning, as outlined below:

1. Cross-Validation Public Records Data
    (a) Aggregate market values in public records datasets are compared to those in the Public Plans Database (PPD).
    (b) Discrepancies are examined using annual reports and are commonly due to:
        i. Exclusion of private assets or commingled funds in public records data.
        ii. PPD coverage is limited to defined benefit plans, while public records data encompass broader plans, such as defined contribution or OPEB/Healthcare Trusts.

C.1.3 Final Cleaning

To construct the final sample used in our empirical analysis, we apply a set of selection criteria to the processed public records data. These criteria are designed to ensure consistency in reporting frequency and comparability with external benchmarks.

1. We retain only pension funds that provide at least five years of quarterly holdings data. Funds that report only annually are excluded.
2. We require a reasonable overlap with the PPD in terms of total asset values and asset composition.
3. Pension funds that omit private assets but otherwise provide comprehensive data are included in the final sample.
4. All other funds—those with inconsistent reporting, insufficient data history, or substantial gaps in key asset classes—are excluded.

After applying these filters, the final sample consists of 65 pension funds. Figure C.1 lays out the coverage of the sample by state.

C.2 Asset Classification Public Records

After the final cleaning step, we need to assign the reported securities to various asset classes, because each pension fund has its own reporting standard, and we thus need to standardize across pension funds. As such, we classified the following asset classes:

1. Equity

   (a) Domestic Equity
   (b) Foreign Equity
2. Fixed Income
   (a) Corporate Bonds
   (b) Government Bonds
   (c) Mortgage-Backed Securities
   (d) Other Fixed Income (e.g., Foreign Government Bonds, Munis, Bank Loans, Convertible Bonds)
3. Cash (including Money Market Funds, T-bills, and Deposits)
4. Repo
5. Mutual Funds
   (a) Equity Funds
   (b) Fixed Income Funds
   (c) Other Funds (e.g., Multi-Asset Funds)
6. Alternatives
   (a) Private Equity (including Infrastructure and Private Credit Funds)
   (b) Real Estate
   (c) Other (e.g., Hedge Funds, Natural Resources, Other Investment Vehicles)
7. Derivatives
   (a) Equity Derivatives
   (b) Fixed Income Derivatives
   (c) Currency Derivatives
   (d) Other Derivatives
   (e) Options

To assign the security holdings to each asset class, we relied as much as we could on the reported asset classes by the pension funds themselves. The provided data can be classified in three categories:

1. Detailed asset classes available
   (a) Cleaning in these instances is straightforward and was mostly based on the classifications pension funds already provided, such as government bonds, MBS, private equity, cash etc.
2. Broad asset classes available
   (a) In some cases, only broad asset categories were provided, such as equity, fixed income, and cash. In these instances, we used security names to assign the holdings to the more granular asset classifications. For instance, if the security name contains "FNMA", we assign it to Mortgage-Backed Securities or if the name contains "Funds", we assign it to Mutual Funds.
3. No asset classes available

(a) Some pension funds did not provide asset classes at all so we had to solely rely on security names. Fortunately, fixed income is straightforward to distinguish from equity because the security names often contain information like maturity date and coupon rates.

For both cases 2) and 3), we used ChatGPT to figure out the security type in case of ambiguities. If that still lead to ambiguity, we would assign it to the asset class "Other". In all three cases, for each pension fund, we made sure to assign each security to one asset class only.

Extracting liquid assets (cash and U.S. Treasuries) is crucial for this paper. Hence, for all cases $1)-3)$, we verified U.S. Treasuries based on security name and/or the provided CUSIP/ISIN numbers. We also ensured in this process that T-bills would be classified as Cash in all instances.

To distinguish between U.S. and foreign equities, we relied on the provided ISIN numbers.

C.3 Asset Characteristics Public Records

We also merge the holdings data to public databases, such as the CRSP and Compustat databases. From these databases, we obtain, among others, security-level returns, dividends, and indicators for foreign stock identifiers.

For 28 out of 64 pension funds, we did not obtain ISIN and/or CUSIP numbers for all quarters. For these cases, we implement a two-stage recovery process to identify the securities.

First, we construct a master "security-name-identifier" database from the broader universe of funds that do report identifiers. We clean this master database by standardizing CUSIPs and ISINs and using reported prices, coupons, and maturities to ensure each security is unique and accurate.

Second, for holdings missing identifiers, we use a fuzzy-string matching algorithm in Python to pair their security names with our master list. We simplify names by expanding abbreviations and removing noise words (like "common" or "inc") to improve match quality. For equities, we require a high name-similarity score; for fixed income, we further validate matches by requiring a consistent maturity date and coupon rate. This allow us to back-fill missing identifiers for the majority of previously unidentified holdings.

Figure C.1: Percentage of Pension Funds Disclosing Holdings by State in 2022

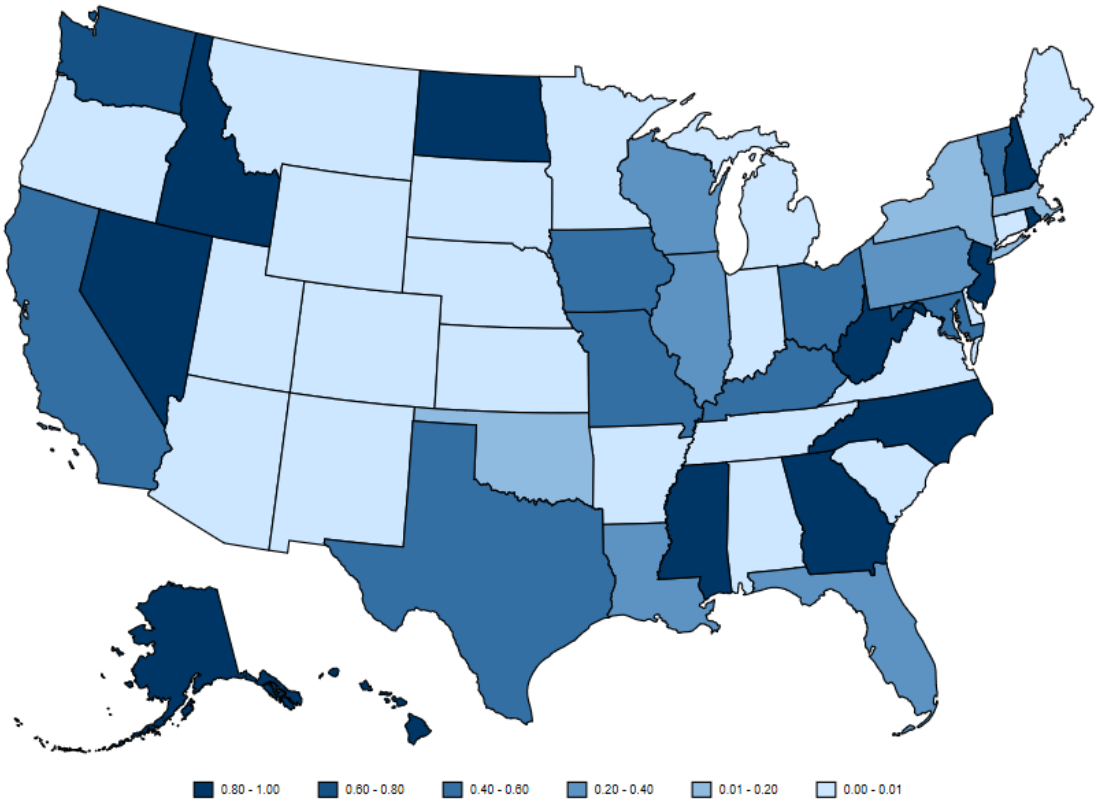


Table C.1: Probability of Pension Funds Disclosing Holdings Data

In this table, observations are at the pension-fund-year level. We present the results of logit specifications and report the marginal effects at the means of the independent variables. *%CF Fit* is the difference between fitted contributions and benefits scaled by pension assets at the beginning of the year. *%CF Residual* is the difference between residual contributions and residual benefits scaled by pension assets. Using piecewise decomposition, we split *%CF Residual* into %CF Residual $\text{Pos}_{i,t} = max(\%\text{CF Residual}_{i,t}, 0)$ and %CF Residual $\text{Neg}_{i,t} = min(\%\text{CF Residual}_{i,t}, 0)$. We control for the lagged log of pension fund size and lagged GASB funding ratio. Return captures the net performance, estimated as the ratio of net investment income to beginning-of-year assets. We control for the target allocation to equity, real assets, hedge funds, private equity, and other risky assets. The specifications include state and reporting-year fixed effects. We cluster standard errors by pension fund, and report standard errors in brackets. $^{*}p < .10$; $^{**}p < .05$; $^{***}p < .01$.

Pension Funds Disclosing Holdings (Unconditional Prob. = 24.4%)						
	(1)	(2)	(3)	(4)	(5)	(6)
%CF	0.459	-0.286				
	[0.477]	[0.858]				
%CF Fit			0.941	-1.596	0.904	-1.625
			[1.321]	[1.966]	[1.325]	[1.962]
%CF Residuals			0.267	0.115		
			[0.275]	[0.288]		
%CF Residuals Pos					0.105	0.053
					[0.340]	[0.285]
%CF Residuals Neg					1.741	0.725
					[2.264]	[2.048]
Pension Fund Size	0.052**	0.080**	0.052**	0.082**	0.051**	0.082**
	[0.020]	[0.033]	[0.020]	[0.034]	[0.020]	[0.034]
GASB Funding Status	0.061	-0.000	0.045	0.026	0.033	0.022
	[0.147]	[0.240]	[0.149]	[0.243]	[0.149]	[0.243]
Return	-0.019	0.415	-0.009	0.388	-0.003	0.392
	[0.361]	[0.423]	[0.360]	[0.415]	[0.363]	[0.419]
%Equity	0.153	0.091	0.167	0.055	0.166	0.052
	[0.369]	[0.460]	[0.374]	[0.453]	[0.373]	[0.453]
%Real Assets	-0.186	-0.443	-0.187	-0.430	-0.195	-0.431
	[0.465]	[0.543]	[0.465]	[0.539]	[0.462]	[0.537]
%Hedge Funds	0.659	0.900	0.666	0.864	0.672	0.866
	[0.442]	[0.559]	[0.445]	[0.559]	[0.444]	[0.560]
%Private Equity	-0.184	-0.217	-0.184	-0.244	-0.183	-0.244
	[0.451]	[0.590]	[0.453]	[0.588]	[0.453]	[0.590]
%Other Alternatives	0.180	0.261	0.173	0.271	0.167	0.272
	[0.511]	[0.660]	[0.507]	[0.662]	[0.506]	[0.662]
Reporting-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
State FE		Yes		Yes		Yes
Observations	3,251	2,458	3,251	2,458	3,251	2,458

Online Appendix D: Pension Fund Aggregate Flows

Table D.1: Asset Class Investment Flows and Cash Flows - Lagged Residual Cash Flows

Robustness test of Table 6: We augment the baseline specification with one-year lags of *%CF Residuals Pos* and *%CF Residuals Neg.*

In this table, observations are at the pension-fund-year level. The dependent variables measure the investment flow of pension fund i in year t into cash & fixed income, equity, or alternatives. *%CF Predicted* is the difference between the predicted contributions and benefits scaled by pension assets at the beginning of the year. *%CF Shock* is estimated using the differences between the realized contributions (benefits) and the predicted contributions (benefits), scaled by pension assets. Using piecewise decomposition, we split *%CF Shock* into %CF Shock $\text{Pos}_{i,t} = max(\%\text{CF Shock}_{i,t}, 0)$ and %CF Shock $\text{Neg}_{i,t} = min(\%\text{CF Shock}_{i,t}, 0)$. We control for the lagged log of pension fund size, lagged GASB funding ratio, and lagged allocation gap. The allocation gap captures the difference between the actual and target asset allocation ($\omega^{Target}_{i,j,t-1} - \omega^{Actual}_{i,j,t-1}$) of pension fund i in asset class j in year $t-1$. The specifications include pension fund and reporting-year fixed effects. We cluster standard errors by pension fund, and report standard errors in brackets. $^{*}p < .10$; $^{**}p < .05$; $^{***}p < .01$.

	Cash & FI		**Equity**		**Alternatives**	
	(1)	(2)	(3)	(4)	(5)	(6)
Mean Dep. Var.	-0.005	-0.005	-0.026	-0.026	0.003	0.003
%CF Fit	0.420***	0.395***	0.505***	0.517***	0.110	0.110
	[0.098]	[0.086]	[0.100]	[0.101]	[0.091]	[0.092]
%CF Residuals Pos	0.782***	0.789***	0.215**	0.208**	0.036*	0.038**
	[0.112]	[0.107]	[0.107]	[0.102]	[0.019]	[0.019]
Lag %CF Residuals Pos		-0.195***		0.197***		-0.020
		[0.064]		[0.049]		[0.022]
%CF Residuals Neg	-0.075	-0.061	0.673***	0.662***	0.415**	0.382**
	[0.107]	[0.137]	[0.141]	[0.117]	[0.173]	[0.170]
Lag %CF Residuals Neg		0.087		-0.086		0.095
		[0.157]		[0.162]		[0.069]
Pension Fund Size	0.009	0.010*	-0.034***	-0.035***	0.021***	0.020***
	[0.006]	[0.006]	[0.007]	[0.007]	[0.007]	[0.007]
GASB Funding Status	-0.022	-0.021	0.001	-0.000	0.014	0.015
	[0.014]	[0.014]	[0.016]	[0.017]	[0.014]	[0.014]
Allocation Gap	0.378***	0.356***	0.367***	0.353***	0.274***	0.273***
	[0.049]	[0.044]	[0.042]	[0.040]	[0.025]	[0.025]
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Pension Fund FE	Yes	Yes	Yes	Yes	Yes	Yes
Reporting-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3,230	3,230	3,230	3,230	3,217	3,217
R-squared	0.451	0.460	0.341	0.350	0.239	0.239

Table D.2: Asset Class Investment Flows and Cash Flows - Alternative CF Decomposition

Robustness test of Table 6: We use the decomposition of cash flows into *%CF Predicted* and *%CF Shock* instead of *%CF Fit* and *%CF Residuals*.

In this table, observations are at the pension-fund-year level. The dependent variables measure the investment flow of pension fund i in year t into cash & fixed income, equity, or alternatives. *%CF Predicted* is the difference between the predicted contributions and benefits scaled by pension assets at the beginning of the year. *%CF Shock* is estimated using the differences between the realized contributions (benefits) and the predicted contributions (benefits), scaled by pension assets. Using piecewise decomposition, we split *%CF Shock* into %CF Shock $\text{Pos}_{i,t} = max(\%\text{CF Shock}_{i,t}, 0)$ and %CF Shock $\text{Neg}_{i,t} = min(\%\text{CF Shock}_{i,t}, 0)$. The reported p-value tests the null that the coefficients on the positive and negative components are equal. We control for the lagged log of pension fund size, lagged GASB funding ratio, and lagged allocation gap. The allocation gap captures the difference between the actual and target asset allocation $(\omega^{Target}_{i,j,t-1} - \omega^{Actual}_{i,j,t-1})$ of pension fund i in asset class j in year $t-1$. The specifications include pension fund and reporting-year fixed effects. We cluster standard errors by pension fund, and report standard errors in brackets. $^{*}p < .10$; $^{**}p < .05$; $^{***}p < .01$.

	Cash & FI		**Equity**		**Alternatives**	
	(1)	(2)	(3)	(4)	(5)	(6)
Mean Dep. Var.	0.000	0.000	-0.031	-0.031	-0.001	-0.001
%CF Predicted	0.310***	0.276***	0.501***	0.502***	0.155*	0.182**
	[0.080]	[0.070]	[0.075]	[0.074]	[0.088]	[0.083]
%CF Shock	0.324***		0.462***		0.171**	
	[0.096]		[0.058]		[0.077]	
%CF Shock Pos		0.480***		0.461***		0.048
		[0.088]		[0.075]		[0.070]
%CF Shock Neg		-0.128		0.466***		0.529***
		[0.128]		[0.083]		[0.118]
Allocation Gap	0.364***	0.365***	0.375***	0.375***	0.272***	0.273***
	[0.040]	[0.040]	[0.037]	[0.037]	[0.029]	[0.029]
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Pension Fund FE	Yes	Yes	Yes	Yes	Yes	Yes
Reporting-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,080	2,080	2,080	2,080	2,078	2,078
R-squared	0.291	0.299	0.325	0.325	0.258	0.261
p-value test		0.00		0.97		0.00

Table D.3: Asset Class Investment Flows and Cash Flows - Public Records Subsample

Robustness test of Table 6: We replicate the analysis for the public records subsample of pension-year observations.

In this table, observations are at the pension-fund-year level. The dependent variables measure the investment flow of pension fund i in year t into cash & fixed income, equity, or alternatives. *%CF Fit* is the difference between fitted contributions and benefits scaled by pension assets at the beginning of the year. *%CF Residual* is the difference between residual contributions and residual benefits scaled by pension assets. Using piecewise decomposition, we split *%CF Residual* into %CF Residual $\text{Pos}_{i,t} = max(\%\text{CF Residual}_{i,t}, 0)$ and %CF Residual $\text{Neg}_{i,t} = min(\%\text{CF Residual}_{i,t}, 0)$. The reported p-value tests the null that the coefficients on the positive and negative components are equal. We control for the lagged log of pension fund size, lagged GASB funding ratio, and lagged allocation gap. The allocation gap captures the difference between the actual and target asset allocation ($\omega_{i,j,t-1}^{Target} - \omega_{i,j,t-1}^{Actual}$) of pension fund i in asset class j in year $t-1$. The specifications include pension fund and reporting-year fixed effects. We cluster standard errors by pension fund, and report standard errors in brackets. $^{*}p < .10$; $^{**}p < .05$; $^{***}p < .01$.

	Cash & FI		**Equity**		**Alternatives**	
	(1)	(2)	(3)	(4)	(5)	(6)
Mean Dep. Var.	-0.001	-0.001	-0.026	-0.026	-0.000	-0.000
%CF Fit	0.276	0.274	-0.050	-0.055	0.344	0.330
	[0.191]	[0.185]	[0.299]	[0.302]	[0.314]	[0.309]
%CF Residuals	0.165*		0.538***		0.263***	
	[0.083]		[0.066]		[0.082]	
%CF Residuals Pos		0.275***		0.574***		0.130
		[0.073]		[0.077]		[0.088]
%CF Residuals Neg		-0.230**		0.411***		0.746***
		[0.107]		[0.104]		[0.086]
Allocation Gap	0.272***	0.277***	0.332***	0.335***	0.245***	0.256***
	[0.099]	[0.101]	[0.047]	[0.047]	[0.038]	[0.037]
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Pension Fund FE	Yes	Yes	Yes	Yes	Yes	Yes
Reporting-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	794	794	794	794	787	787
R-squared	0.281	0.288	0.376	0.377	0.346	0.355
p-value test		0.00		0.26		0.00

Table D.4: Asset Class Investment Flows and Cash Flows - Dividends and Interest

Robustness test of Table 6: We control for the investment income from interest payments and dividends. We scale the dividends and interest income by pension assets at the beginning of the year.

In this table, observations are at the pension-fund-year level. The dependent variables measure the investment flow of pension fund i in year t into cash & fixed income, equity, or alternatives. *%CF Fit* is the difference between fitted contributions and benefits scaled by pension assets at the beginning of the year. *%CF Residual* is the difference between residual contributions and residual benefits scaled by pension assets. Using piecewise decomposition, we split *%CF Residual* into %CF Residual $\text{Pos}_{i,t} = max(\%\text{CF Residual}_{i,t}, 0)$ and %CF Residual $\text{Neg}_{i,t} = min(\%\text{CF Residual}_{i,t}, 0)$. The reported p-value tests the null that the coefficients on the positive and negative components are equal. We control for the lagged log of pension fund size, lagged GASB funding ratio, and lagged allocation gap. The allocation gap captures the difference between the actual and target asset allocation ($\omega_{i,j,t-1}^{Target} - \omega_{i,j,t-1}^{Actual}$) of pension fund i in asset class j in year $t-1$. The specifications include pension fund and reporting-year fixed effects. We cluster standard errors by pension fund, and report standard errors in brackets. $^*p < .10$; $^{**}p < .05$; $^{***}p < .01$.

	Cash & FI		**Equity**		**Alternatives**	
	(1)	(2)	(3)	(4)	(5)	(6)
Mean Dep. Var.	-0.006	-0.006	-0.026	-0.026	0.003	0.003
%CF Fit	0.429***	0.451***	0.453***	0.449***	0.064	0.049
	[0.105]	[0.107]	[0.122]	[0.121]	[0.113]	[0.114]
%CF Residuals	0.447***		0.481***		0.086*	
	[0.065]		[0.047]		[0.045]	
%CF Residuals Pos		0.565***		0.453***		0.009
		[0.071]		[0.065]		[0.043]
%CF Residuals Neg		0.009		0.584***		0.376**
		[0.108]		[0.100]		[0.144]
Allocation Gap	0.344***	0.348***	0.332***	0.333***	0.250***	0.252***
	[0.050]	[0.050]	[0.048]	[0.048]	[0.025]	[0.026]
Dividends Interest Income	0.103	0.121	0.185*	0.181*	-0.010	-0.023
	[0.084]	[0.088]	[0.098]	[0.097]	[0.091]	[0.094]
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Pension Fund FE	Yes	Yes	Yes	Yes	Yes	Yes
Reporting-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,430	2,430	2,430	2,430	2,420	2,420
R-squared	0.369	0.375	0.356	0.356	0.244	0.248
p-value test		0.00		0.35		0.03

Table D.5: Asset Class Investment Flows and Cash Flows - Investment Income

Robustness test of Table 6: We control for the investment income. Investment income is part of the investment returns. It is defined as income from interest payments, dividends, limited partnerships, and securities lending, net of investment expenses. We scale the investment income by pension assets at the beginning of the year.

In this table, observations are at the pension-fund-year level. The dependent variables measure the investment flow of pension fund i in year t into cash & fixed income, equity, or alternatives. *%CF Fit* is the difference between fitted contributions and benefits scaled by pension assets at the beginning of the year. *%CF Residual* is the difference between residual contributions and residual benefits scaled by pension assets. Using piecewise decomposition, we split *%CF Residual* into %CF Residual $\text{Pos}_{i,t} = max(\%\text{CF Residual}_{i,t}, 0)$ and %CF Residual $\text{Neg}_{i,t} = min(\%\text{CF Residual}_{i,t}, 0)$. The reported p-value tests the null that the coefficients on the positive and negative components are equal. We control for the lagged log of pension fund size, lagged GASB funding ratio, and lagged allocation gap. The allocation gap captures the difference between the actual and target asset allocation ($\omega_{i,j,t-1}^{Target} - \omega_{i,j,t-1}^{Actual}$) of pension fund i in asset class j in year $t-1$. The specifications include pension fund and reporting-year fixed effects. We cluster standard errors by pension fund, and report standard errors in brackets. $^{*}p < .10$; $^{**}p < .05$; $^{***}p < .01$.

	Cash & FI		**Equity**		**Alternatives**	
	(1)	(2)	(3)	(4)	(5)	(6)
Mean Dep. Var.	-0.006	-0.006	-0.026	-0.026	0.003	0.003
%CF Fit	0.418***	0.444***	0.439***	0.435***	0.131	0.111
	[0.099]	[0.102]	[0.122]	[0.121]	[0.121]	[0.118]
%CF Residuals	0.443***		0.482***		0.101*	
	[0.064]		[0.046]		[0.057]	
%CF Residuals Pos		0.560***		0.464***		0.009
		[0.069]		[0.064]		[0.043]
%CF Residuals Neg		0.017		0.549***		0.435**
		[0.107]		[0.105]		[0.179]
Allocation Gap	0.341***	0.344***	0.345***	0.345***	0.262***	0.264***
	[0.048]	[0.048]	[0.047]	[0.047]	[0.026]	[0.026]
Investment Income	0.135**	0.140**	0.210**	0.210**	0.014	0.011
	[0.063]	[0.062]	[0.095]	[0.095]	[0.076]	[0.076]
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Pension Fund FE	Yes	Yes	Yes	Yes	Yes	Yes
Reporting-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,614	2,614	2,614	2,614	2,601	2,601
R-squared	0.371	0.377	0.361	0.361	0.241	0.245
p-value test		0.00		0.56		0.03

Table D.6: Asset Class Investment Flows and Cash Flows - Rebalancing Flows

Robustness test of Table 6: We control for the difference in returns between equities and fixed income ($R^{BM}_{EQ,t} - R^{BM}_{FI,t}$) instead of including reporting-year fixed effects. $R^{BM}_{j,t}$ is the median return of all pension funds that operate with the same fiscal year end in asset class j in year t.

In this table, observations are at the pension-fund-year level. The dependent variables measure the investment flow of pension fund i in year t into cash & fixed income, equity, or alternatives. *%CF Fit* is the difference between fitted contributions and benefits scaled by pension assets at the beginning of the year. *%CF Residual* is the difference between residual contributions and residual benefits scaled by pension assets. Using piecewise decomposition, we split *%CF Residual* into %CF Residual Pos$_{i,t} = max$(%CF Residual$_{i,t}, 0$) and %CF Residual Neg$_{i,t} = min$(%CF Residual$_{i,t}, 0$). The reported p-value tests the null that the coefficients on the positive and negative components are equal. We control for the lagged log of pension fund size, lagged GASB funding ratio, and lagged allocation gap. The allocation gap captures the difference between the actual and target asset allocation ($\omega^{Target}_{i,j,t-1} - \omega^{Actual}_{i,j,t-1}$) of pension fund i in asset class j in year $t-1$. The specifications include pension fund fixed effects. We cluster standard errors by pension fund, and report standard errors in brackets. $^{*}p < .10$; $^{**}p < .05$; $^{***}p < .01$.

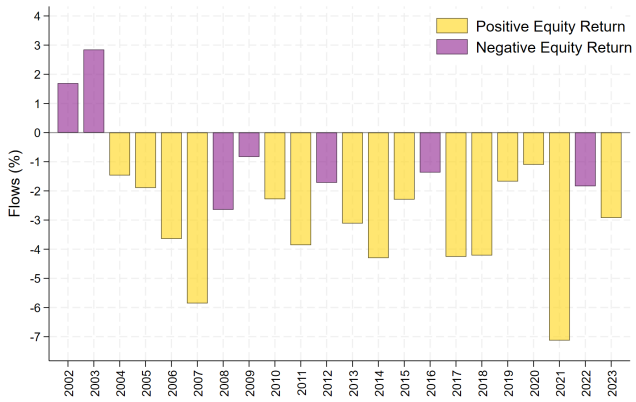
	Cash & FI		**Equity**		**Alternatives**	
	(1)	(2)	(3)	(4)	(5)	(6)
Mean Dep. Var.	-0.005	-0.005	-0.026	-0.026	0.003	0.003
%CF Fit	0.359***	0.422***	0.582***	0.549***	0.049	0.020
	[0.100]	[0.097]	[0.122]	[0.110]	[0.108]	[0.101]
%CF Residuals	0.687***		0.270**		0.059*	
	[0.127]		[0.115]		[0.033]	
%CF Residuals Pos		0.774***		0.223*		0.020
		[0.112]		[0.119]		[0.019]
%CF Residuals Neg		-0.027		0.655***		0.381**
		[0.118]		[0.157]		[0.192]
Allocation Gap	0.390***	0.394***	0.357***	0.359***	0.248***	0.248***
	[0.046]	[0.046]	[0.035]	[0.035]	[0.024]	[0.025]
$R^{BM}_{EQ,t} - R^{BM}_{FI,t}$	0.089***	0.089***	-0.073***	-0.073***	0.007	0.007
	[0.005]	[0.005]	[0.006]	[0.006]	[0.004]	[0.004]
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Pension Fund FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3,252	3,252	3,257	3,257	3,243	3,243
R-squared	0.409	0.421	0.293	0.297	0.146	0.149
p-value test		0.00		0.08		0.07

Figure D.1: Annual Equity Flows Based on the Aggregate Pension Sample

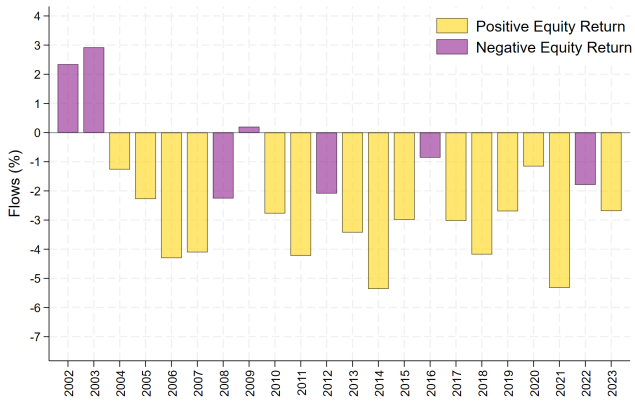
Robustness test of Figure 4: Instead of aggregating across all pension funds, we estimate the annual equity flows separately for pension funds with fiscal-year-ends in June and December. June and December are the two main reporting dates and cover 94% of the observations.

This figure shows the flows into equities by year. Flows into equities for pension fund i are computed as $Flow_{i,j,t} = \frac{A_{i,j,t} - A_{i,j,t-1} \times (1+R^{BM}_{j,t})}{TA_{i,t-1}}$, where $A_{i,j,t}$ is the dollar amount invested by pension fund i in equity j in year t, $TA_{i,t-1}$ is the total amount of assets under management, and $R^{BM}_{j,t}$ is the median return of all pension funds that operate with the same fiscal year end in equity j in year t. Since pension funds have different fiscal-year-ends, they do not experience identical equity market returns at reporting dates. Therefore, we estimate the annual equity flows separately for pension funds with fiscal-year-ends in June and December. We report the annual flows for the aggregate across pension funds (value-weighted average, Panels A and C) and for the average pension fund (Panels B and D) in our sample. For the value-weighted averages, we use the beginning-of-year total assets as weights.

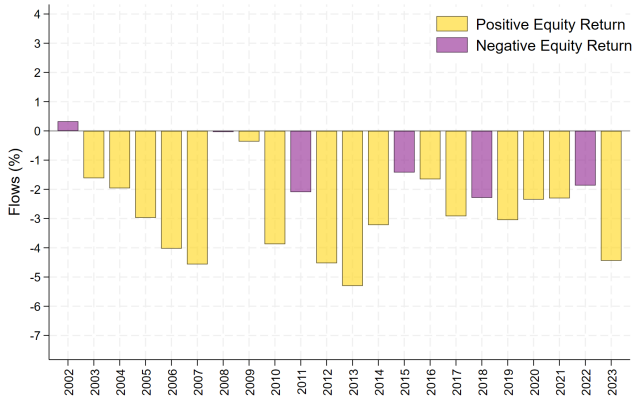
Panel A: Total June Pension Funds



Panel B: Average June Pension Fund



Panel C: Total December Pension Funds



Panel D: Average December Pension Funds

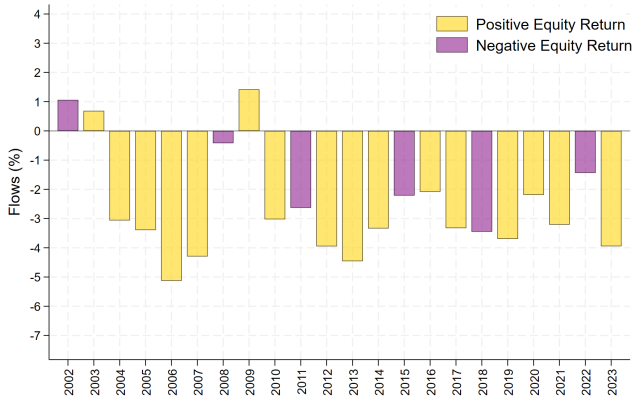


Table D.7: Investment Flows and Cash Flows by Lagged GASB Funding Ratio Tertiles

In this table, observations are at the pension-fund-year level. The dependent variable measures the investment flow of pension fund i in year t into equity (Panel A) and cash & fixed income (Panel B). We split pension funds into tertiles based on the lagged GASB Funding Ratio. We report results for the high and low tertiles. *%CF Fit* is the difference between fitted contributions and benefits scaled by pension assets at the beginning of the year. *%CF Residual* is the difference between residual contributions and residual benefits scaled by pension assets. Using piecewise decomposition, we split *%CF Residual* into %CF Residual $\text{Pos}_{i,t} = max(\%\text{CF Residual}_{i,t}, 0)$ and %CF Residual $\text{Neg}_{i,t} = min(\%\text{CF Residual}_{i,t}, 0)$. The reported p-value tests the null that the coefficients on the positive and negative components are equal. We control for the lagged log of pension fund size, lagged GASB funding ratio, and lagged allocation gap. The specifications include pension fund and reporting-year fixed effects. We cluster standard errors by pension fund, and report standard errors in brackets. $^{*}p < .10$; $^{**}p < .05$; $^{***}p < .01$.

	Low		**High**	
	(1)	(2)	(3)	(4)
Panel A: Equity Investment Flows				
Mean Dep. Var.	-0.025	-0.025	-0.026	-0.026
%CF Fit	0.555***	0.498***	0.321	0.306
	[0.102]	[0.092]	[0.396]	[0.394]
%CF Residuals	0.213**		0.484***	
	[0.097]		[0.128]	
%CF Residuals Pos		0.178*		0.435***
		[0.093]		[0.144]
%CF Residuals Neg		0.590***		0.776**
		[0.125]		[0.369]
Allocation Gap	0.338***	0.335***	0.395***	0.394***
	[0.060]	[0.059]	[0.090]	[0.090]
Controls	Yes	Yes	Yes	Yes
Pension Fund FE	Yes	Yes	Yes	Yes
Reporting-Year FE	Yes	Yes	Yes	Yes
Observations	1,082	1,082	997	997
R-squared	0.397	0.401	0.361	0.361
p-value test		0.03		0.42
Panel B: Cash and Fixed Income Investment Flows				
Mean Dep. Var.	-0.004	-0.004	-0.006	-0.006
%CF Fit	0.468***	0.604***	-0.048	-0.032
	[0.130]	[0.127]	[0.326]	[0.328]
%CF Residuals	0.749***		0.472***	
	[0.123]		[0.098]	
%CF Residuals Pos		0.826***		0.524***
		[0.099]		[0.098]
%CF Residuals Neg		-0.094		0.164
		[0.128]		[0.249]
Allocation Gap	0.357***	0.369***	0.385***	0.384***
	[0.072]	[0.071]	[0.096]	[0.096]
Controls	Yes	Yes	Yes	Yes
Pension Fund FE	Yes	Yes	Yes	Yes
Reporting-Year FE	Yes	Yes	Yes	Yes
Observations	1,082	1,082	997	997
R-squared	0.532	0.552	0.409	0.410
p-value test		0.00		0.17

Online Appendix E: Extra Results Pension Fund Holdings Data

Table E.1: Asset Allocation to Cash and U.S. Treasuries and Cash Flows - Cash vs. Treasuries

Robustness test of Table 5: We split the dependent variable into separate allocations to cash (Panel A) and U.S. Treasuries (Panel B).

In this table, observations are at the pension fund-year level. The dependent variable equals the actual allocation to either cash (Panel A) or U.S. Treasury securities (Panel B) based on the holdings data obtained through public records requests. Cash includes T-bills, money market funds, and bank deposits. *%CF* is the ratio of net cash flows to pension fund assets at the beginning of the year. *%CF Fit* is the difference between fitted contributions and benefits scaled by pension assets. *%CF Predicted* is the difference between the predicted contributions and benefits scaled by pension assets. *%CF Volatility* is the volatility of *%CF* over the previous 10 years. We control for the lagged log of pension fund size and the lagged GASB funding ratio. The specifications include reporting-year fixed effects. We cluster standard errors by pension fund, and report standard errors in brackets. $^{*}p < .05$; $^{**}p < .01$; $^{***}p < .001$.

	(1)	(2)	(3)	(4)
Panel A: Allocation to Cash				
Mean Dep. Var.	0.040	0.040	0.037	0.037
%CF	-0.066			
	[0.130]			
%CF Fit		-0.199		
		[0.227]		
%CF Predicted			-0.096	
			[0.159]	
%CF Volatility				0.157
				[0.130]
Controls	Yes	Yes	Yes	Yes
Reporting-Year FE	Yes	Yes	Yes	Yes
Observations	840	840	652	652
R-squared	0.076	0.083	0.057	0.058
Panel B: Allocation to U.S. Treasuries				
Mean Dep. Var.	0.063	0.063	0.064	0.064
%CF	-0.287			
	[0.226]			
%CF Fit		-0.605		
		[0.437]		
%CF Predicted			-0.465	
			[0.324]	
%CF Volatility				-0.206
				[0.184]
Controls	Yes	Yes	Yes	Yes
Reporting-Year FE	Yes	Yes	Yes	Yes
Observations	840	840	652	652
R-squared	0.119	0.134	0.121	0.101

Table E.2: Income from Dividends and Coupons and Cash Flows - Dividends vs. Coupons

Robustness test of Table 7: We split the total investment income into dividends relative to equity assets (Panel A) and coupons relative to fixed income assets (Panel B).

In this table, observations are at the pension fund-year level. The dependent variable equals the investment income from dividends payments relative to equity assets (Panel A) or from coupons relative to fixed income assets (Panel B), based on the holdings data obtained through public records requests. *%CF* is the ratio of net cash flows to pension fund assets at the beginning of the year. *%CF Fit* is the difference between fitted contributions and benefits scaled by pension assets. *%CF Predicted* is the difference between the predicted contributions and benefits scaled by pension assets. *%CF Volatility* is the volatility of *%CF* over the previous 10 years. We control for the lagged log of pension fund size and the lagged GASB funding ratio. The specifications include reporting-year fixed effects. We cluster standard errors by pension fund, and report standard errors in brackets. $^{*}p < .05$; $^{**}p < .01$; $^{***}p < .001$.

	(1)	(2)	(3)	(4)
Panel A: Dividends (relative to equity assets)				
Mean Dep. Var.	1.906	1.906	1.923	1.923
%CF	0.013			
	[0.030]			
%CF Fit		0.006		
		[0.050]		
%CF Predicted			0.018	
			[0.038]	
%CF Volatility				0.027
				[0.049]
Controls	Yes	Yes	Yes	Yes
Reporting-Year FE	Yes	Yes	Yes	Yes
Observations	804	804	645	645
R-squared	0.197	0.196	0.171	0.171
Panel B: Coupons (relative to fixed income assets)				
Mean Dep. Var.	3.621	3.621	3.330	3.330
%CF	-0.020			
	[0.026]			
%CF Fit		-0.042		
		[0.040]		
%CF Predicted			-0.005	
			[0.030]	
%CF Volatility				0.014
				[0.037]
Controls	Yes	Yes	Yes	Yes
Reporting-Year FE	Yes	Yes	Yes	Yes
Observations	804	804	645	645
R-squared	0.380	0.383	0.139	0.140

Online Appendix F: Case Study of the Dallas Police & Fire Pension System Liquidity Crisis

The Dallas Police & Fire Pension System (DPFP) provides a useful case study of how extreme negative cash flow shocks affect the selling behavior of pension funds. During 2016, the fund faced a liquidity crisis driven by massive retirement account withdrawals from the Deferred Retirement Option Plan (DROP) due to concerns over the funding status of DPFP and the sustainability of these DROP accounts.

As illustrated in the Figure F.1, the magnitude of this shock was severe: the total cash outflow equaled -26% of total assets, of which 22% was unexpected. In total, members withdrew over $600 million in lump sum payments from their DROP balances during the 2016 fiscal year, a large increase compared to only $81 million in 2015 (Dallas Police & Fire Pension System, 2017).

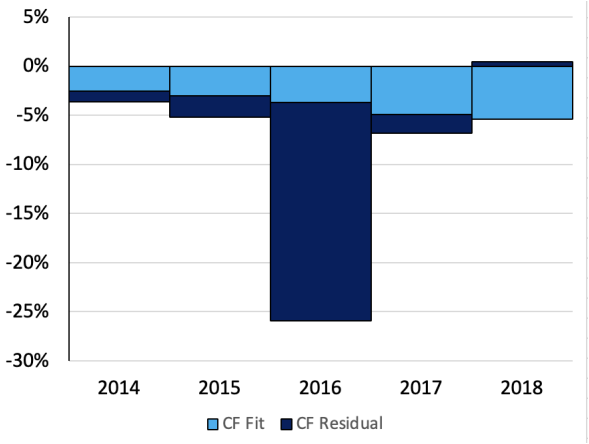
To meet these liquidity demands, the fund was forced to sell assets. Right before the liquidity run in 2015Q4, the DPFP asset allocation was comprised of 10.3% fixed income, 1.5% cash, 15.7% equities, 41.6% alternatives (private equity and real estate), and 30.9% in other risky assets, including investment funds and hedge funds. During the run, the fund started by primarily liquidating its equity holdings, which resulted in a significant reduction of that asset class to about half the size of its 2015Q4 allocation. During 2016, the system also sold other risky assets equal to approximately 12% of total assets.

As the run intensified towards the end of 2016, Dallas also sold a large share of their alternative assets. The sales of alternative assets is also mentioned in DPFP annual report (Dallas Police & Fire Pension System, 2017): "In December 2016, the Board approved the sale of 26 fund investments across the Private Equity, Private Debt and Real Estate portfolios which resulted in proceeds of approximately $246 million and reduced unfunded commitments by approximately $130 million." Further liquidity was raised through the direct sale of seven real estate assets located in Arizona, Texas, Idaho, Hawaii, and the Bahamas, which generated an additional $57 million in proceeds.

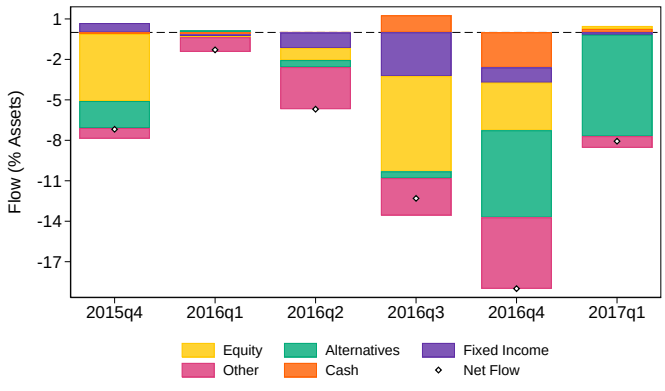
Measured over 2016Q1–2016Q4, cumulative sales equaled 11.6% of assets for equities, 7.3% for alternatives, and 12.2% for other risky assets. DPFP also sold fixed income securities equal to 5.6% of assets, a substantially smaller amount than its sales of risky assets. In 2016Q4, the fund also used cash that was part of the proceeds from these earlier asset sales to meet withdrawal demands.

Figure F.1: Cash Flows and Investment Flows Dallas Police & Fire Pension System Run

Panel A shows the fitted and residual cash flows for the Dallas Police & Fire Pension System during the pension fund run in 2016. Panel B shows the respective investment flows to several asset classes during the run: equity, alternatives (private equity and real estate), fixed income, other (hedge funds and investment funds), and cash.



Panel A: Cash Flows



Panel B: Investment Flows

Online Appendix G: Public Records/PPD Analysis versus Equity Flows Implied by the Federal Reserve Flow of Funds

Our findings of equity sales during periods of market stress may seem at odds with those of Gabaix and Koijen (2023), who show using Federal Reserve Flow of Funds data that during the dotcom bubble and the GFC, state and local pension funds (together with foreign investors) bought equities while other investors sold. While we also find equity purchases during the dotcom bubble crash, we find that during most quarters of the GFC, pension funds were selling, rather than buying, equities.

The data in Gabaix and Koijen (2023) is based on Flow of Funds (FoF) data from the Federal Reserve's Financial Accounts of the United States, while we rely on public records requests and the PPD database. Indeed, Figure G.1 indicates that state and local pension funds were buying equities during the GFC based on the FoF data. This appendix details the discrepancies in estimated equity flows of pension funds between the FoF and our datasets.

Federal Reserve Flow of Funds Methodology

The Federal Reserve derives equity flows (Series FU223064145) for state and local pension funds primarily by benchmarking to the U.S. Census Bureau's Annual Survey of Public Pensions (ASPP) and the Quarterly Survey of Public Pensions (QSPP). FoF does not use holdings data and does not measure transactions directly for the pre-2019 period. Instead, it calculates flows (or transactions) as a residual: Transactions = ΔLevels − Capital Gains − Other Changes in Volume.

Key Assumptions Used by the Federal Reserve (Pre-2019Q1)

1. Asset Mapping: Consistent with the standard classification in the Financial Accounts guide, the FoF defines corporate equity to encompass both public and private equity as a single category. Corporate equity holdings are estimated as the sum of the ASPP corporate stocks line item (which includes common and preferred stocks, warrants, and private equity) plus 75–80% of "miscellaneous investments," with the latter attributed to private equity funds based on manual data collection from a subsample of Comprehensive Annual Financial Reports (CAFRs). The FoF also allocates 85% of foreign assets to equities.

2. Capital Gains Estimation: Capital gains are imputed using the quarterly growth rate of the Dow Jones U.S. Total Market Index for domestic equities and the Morgan Stanley World ex U.S. Stock Index for foreign equities.

3. The QSPP Bridge: Levels between annual benchmarks are interpolated using the growth rate of QSPP corporate stocks.

Sources of Discrepancy

While the FoF asset mapping methodology could work well for periods when pension funds held stable and simpler portfolios of domestic equities and bonds, it can lead to a mismatch between what the FoF equity flow series measures and what our data captures in periods when pension funds shift their allocation from public equities to private markets. The FoF series (FU223064145) reflects combined corporate equity flows, spanning both public and private equity by construction. Thus, it cannot distinguish between flows in public and private equities, and cannot be used to infer flows just to public equity in periods with changing allocations, whereas our analysis focuses specifically on transactions in publicly traded equities.

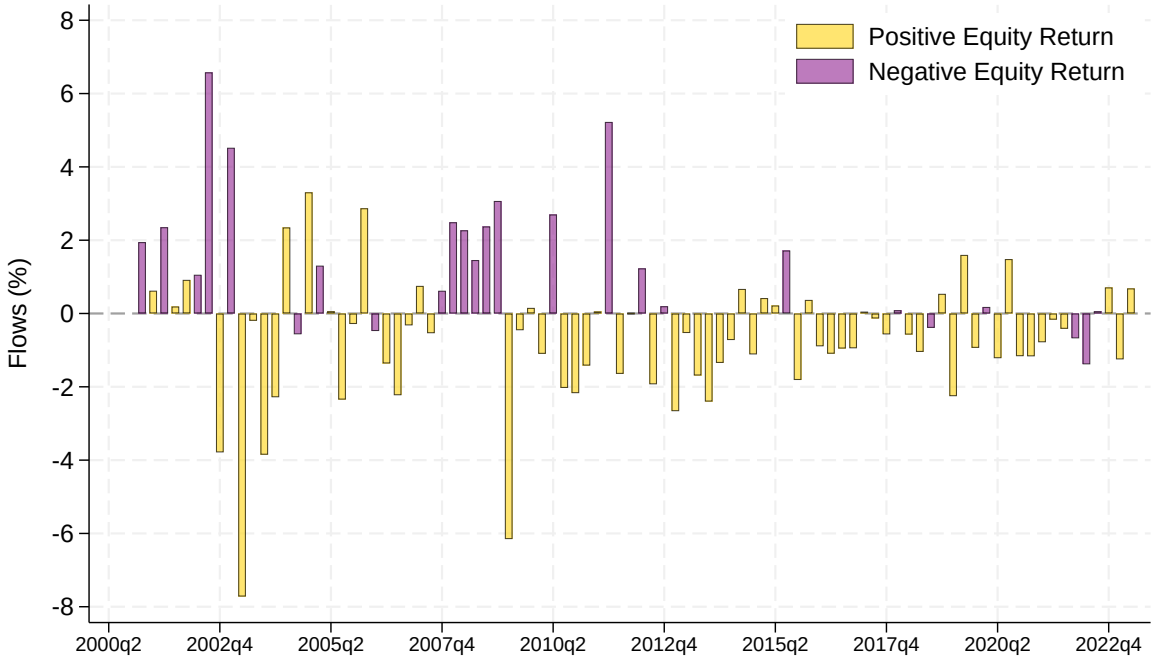
This distinction is particularly consequential for the GFC period. In the years surrounding the GFC, state and local pension funds significantly increased their allocations to private equity and other alternative asset classes. Because the FoF methodology includes private equity in its corporate equity definition, the secular growth in private equity commitments appears in the FoF series as rising equity levels and, after

netting out capital gains, as net equity purchases. Our public records and PPD data, which track holdings of publicly traded stocks, would simultaneously show outflows from public equities. The two series are therefore not directly comparable: the FoF shows corporate equity purchases during the GFC even though funds were actively reducing their public equity exposure.

Assumptions 2 and 3 could also contribute to discrepancies. The Dow Jones U.S. Total Market Index and the Morgan Stanley World ex U.S. Stock Index may not be representative of the specific equity portfolios held by pension funds, while our holdings-based analysis precisely measures the exposure and performance that pension funds actually experienced.

Figure G.1: Equity Flows Implied by the Federal Reserve Flow of Funds

This plot shows the estimated equity flows (as a percentage of beginning-of-quarter total assets) for state and local defined benefit pension funds in the FoF during periods of positive and negative equity returns, as a contrast to our PPD and public records analysis in Figure 4. The equity flow series is obtained from FRED (FU223064145) and scaled by beginning-of-quarter total assets (FL224090045 minus FL223073045). Investable assets are defined by subtracting the unfunded "claim on sponsor" (FL223073045) from the total financial assets (FL224090045) reported in the Z.1 Financial Accounts, as the former represents an accounting accrual rather than financial assets.



Online Appendix H: External Validity of Negative Cash Flows

This appendix provides evidence that negative cash flows are not unique to U.S. public pension funds. We examine two additional groups of long-horizon institutional investors: Canadian public pension funds and U.S. university endowments. In both cases, we measure net cash flows as a percentage of assets and report the median, equal-weighted average, and value-weighted average across institutions.

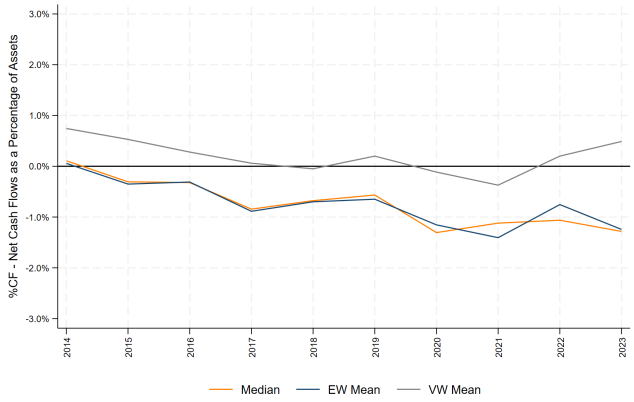
Panel A of Figure H.1 shows the cash flows of Canadian public pension funds. The sample includes 27 public pension plans with CAD 1.86 trillion in assets in 2023. Cash flows become negative during the 2014–2023 period for both the median and equal-weighted average pension fund.[26] The value-weighted average is higher, reflecting the influence of the Canada Pension Plan, which has CAD 0.57 trillion in assets in 2023, but it also declines over the period.

Panel B shows the cash flows of U.S. university endowments. The sample includes 29 endowments with USD 0.37 trillion in assets in 2023. In contrast to Canadian public pension funds, endowment cash flows are negative throughout the sample period. The value-weighted average is generally below the median and equal-weighted average, indicating that the largest endowments are more cash-flow negative. The equal-weighted average is more volatile because some universities receive large donations in individual years. For example, the 2019 spike reflects the $1.8 billion donation from Mike Bloomberg to Johns Hopkins University, which represented 45% of the university's endowment assets.

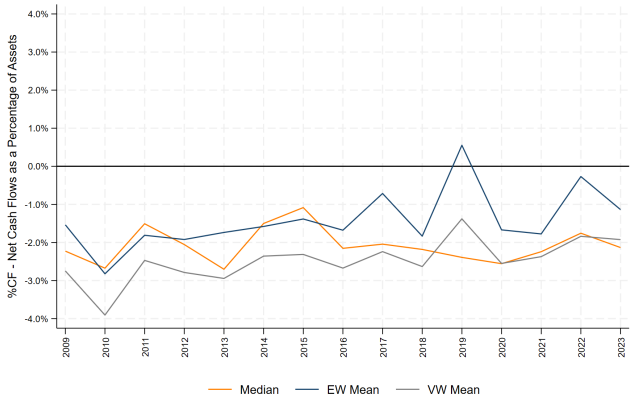
Overall, the evidence in this appendix shows that persistent negative cash flows are a broader feature of mature institutional investors. The magnitudes for U.S. university endowments are close to the -2.4% level observed for U.S. public pension funds, while Canadian public pension funds have moved from positive toward negative cash flows over the last decade.

Figure H.1: Cash Flows of Canadian Public Pension Funds and U.S. University Endowments

This figure shows net cash flows as a percentage of assets for Canadian public pension funds and U.S. university endowments. Panel A reports the median, equal-weighted average, and value-weighted average for 27 Canadian public pension plans with CAD 1.86 trillion in assets in 2023. Panel B reports the same statistics for 29 U.S. university endowments with USD 0.37 trillion in assets in 2023.



Panel A: Canadian Public Pension Funds



Panel B: U.S. University Endowments

[26] To maintain a balanced panel, we start the figure in 2014 as data for all Alberta and Quebec plans are available from that year onward.