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

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Abstract

U.S. public pension funds increasingly face negative net operating cash flows as benefit payments exceed contributions. We study how these funds incorporate cash flows into their asset allocation and investment decisions using aggregate pension fund data and granular holdings data obtained through FOIA requests. While asset allocation models predict that investors should accommodate negative cash flows by adopting more conservative portfolios, we show empirically that target allocations are independent of cash flows. Instead, negative cash flows make pension funds predictable net sellers and liquidity demanders in financial markets. Pension funds accommodate predictable negative cash flows by selling fixed income and equities, but they meet negative cash flow shocks by liquidating equities and even alternative assets. These liquidity-driven sales of equities occur even during periods of negative equity returns, which confirms that liquidity sales are separate from portfolio rebalancing. At the security level, pension funds follow a pecking order of liquidity by selling more of their liquid equities. Yet, funds more exposed to alternatives rely disproportionately on equity and illiquid equity sales to meet liquidity needs.

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1 Introduction

Pension funds in traditional defined benefit plans provide benefit payments to retirees based on their salaries and years of service. Given this predictable long-term liability structure, pension funds are typically modeled as long-horizon investors who do not face pressure to adjust their portfolios in response to short-term market fluctuations (e.g., Campbell and Viceira, 2002; Cochrane, 2022). Thus, much finance literature perceives pension funds as long-term investors that 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).

However, even if the average duration of pension fund cash flows is medium to long term, we find that most U.S. public pension funds are cash flow negative investors on an operating basis. That is, their inflows from contributions are smaller than their outflows for benefit payments and administrative expenses. This cash flow shortfall implies that pension funds need to liquidate part of their portfolio to meet obligations. Such entities would then become regular net sellers in financial markets.

The goal of this paper is to understand how pension funds incorporate negative cash flows in their asset allocation decisions. Our first contribution is to show that negative cash flows are not reflected in pension funds' target asset allocations, even though financial theory suggests that investors should adopt more conservative portfolios when faced with persistent cash outflows due to life-cycle considerations, payout concerns, or liability hedging (e.g., Sharpe and Tint, 1990; Viceira, 2001; Ang, Papanikolaou, and Westerfield, 2014; Campbell, Stein, and Wu, 2024). Our second contribution is to show that pension funds have become regular sellers in equity markets. Pension funds accommodate predictable negative cash flows by selling fixed income and equities in proportion to their target weights. However, they absorb unexpected cash flow shocks by liquidating equities and even alternative assets, including private equity, as they lack sufficient buffers of liquid assets to

meet such shocks.

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 FOIA 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 57 pension funds that cover approximately 40% of total pension assets, our FOIA data provides detailed quarterly holdings across equities, fixed income, cash, alternatives, and derivatives, allowing us to study how funds adjust portfolios on a security level when facing cash flow shocks.

Pension fund net operating cash flows are defined as the difference between the contribution inflows and the 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 the cash flows into predictable (fitted) and residual components using a two-step detrending procedure. First, we regress contributions and benefits of each pension fund separately on a time trend using robust regressions that reduce the influence of outliers to estimate the fitted and residual values. Second, we construct predictable cash flows as the difference between fitted contributions and fitted benefits, and residual cash flows as residual contributions minus residual benefits, scaled by assets. This decomposition allows us to distinguish predictable trends from shocks in pension fund cash flows.

We begin by studying whether pension funds incorporate cash flows in their asset allocation decisions. Financial theory suggests they should. First, life-cycle and ALM models suggest 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). Second, the payout policy literature argues that mature pension funds are more asset-dependent in their operations and should hold a conservative portfolio (Campbell et al., 2024).

This *liquidity buffer hypothesis* predicts that pension funds maintain sufficient liquid holdings to absorb negative cash flows. When they face (unexpected) outflows, pension funds follow a pecking order by selling their 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; Ma, Xiao, and Zeng, 2022).

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). Pension funds may perceive the cost of forgoing higher returns on risky assets to outweigh the costs of selling those assets when liquidity needs arise. Instead, they meet liquidity needs through *pro-rata selling*, liquidating assets proportionally across asset classes to preserve allocations despite differences in liquidity and volatility across assets. In practice, pro-rata selling may be limited, with pension funds meeting cash-flow needs mainly through equities and fixed income while leaving illiquid alternatives largely untouched.

We first examine whether pension funds incorporate differences in operating cash flows in their target asset allocations. The liquidity buffer hypothesis predicts that funds facing lower or more volatile cash flows should have larger allocations to safe and liquid assets, such as cash and fixed income, and smaller allocations to illiquid alternatives. Contrary to this hypothesis, 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 weaker predictable cash flows do not increase allocations to cash and fixed income, nor do they reduce allocations to alternatives.

Using the FOIA holdings data, we examine directly the allocation to cash and U.S. Treasuries, which are the least volatile and most liquid assets in pension portfolios. This analysis confirms that pension funds do not adjust allocations in response to cash flow positions. On average, pension funds maintain limited liquidity buffers, with cash and Treasuries representing only 9% of total assets.

Despite persistent negative operating cash flows, pension funds appear to set target allocations independently of liquidity considerations. The evidence suggests that pension funds perceive the opportunity cost of forgoing higher expected returns on risky 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 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 different asset classes.

We find that pension funds do not respond to predictable negative cash flows in line with the liquid-assets-first hypothesis, as investment 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 pension fund portfolio composition or risk.

In contrast, pension fund responses to unpredictable cash flows are asymmetric and deviate from both liquid-assets-first and pro-rata hypotheses. Funds absorb modest positive residual cash inflows by constrained pro-rata investments, while they absorb large cash inflows primarily by cash and fixed income assets. However, negative residual cash outflows lead to substantial sales of equities (around \$0.67 per \$1) and alternatives (\$0.41 per \$1), while cash and fixed income remain largely unaffected.

We argue that pension funds deviate from pro-rata selling when facing negative shocks because they hold low liquidity buffers, forcing them to sell equities. The 9% of pension fund assets in cash

and U.S. Treasuries can be quickly depleted.[1] 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, pension funds with limited liquidity buffers sell more equities in response to negative cash flow shocks, confirming that cash shortfalls are absorbed through equity sales.

Using the FOIA holdings data, we can 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. We are particularly interested in whether pension funds sell fewer illiquid stocks when faced with cash flow shocks to test the liquid-assets-first 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.

For the full FOIA sample, we find that pension funds do not disproportionately sell fewer illiquid stocks when faced with negative cash flow shocks, inconsistent with the liquid-assets-first hypothesis but consistent with pro-rata flows within equities. However, heterogeneity across pension funds reveals that those with high allocations to alternatives sell disproportionately fewer illiquid stocks when faced with cash flow shocks, which is consistent with a strategy that combines pro-rata flows with the liquid-assets-first hypothesis. Quantitatively, pension funds are 58% less likely to sell illiquid than liquid stocks. Despite this tendency, the selling of illiquid stocks remains substantial and well above the average sales of liquid stocks for pension funds with lower allocations to alternatives. This result implies that pension funds likely face nontrivial costs from selling equities.

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

[1] In addition to benefit payments, pension funds also need liquidity to cover uncalled capital commitments to private equity funds and margin calls on derivatives.

gap and time fixed effects. The allocation gap captures pension funds' gradual adjustments of actual allocation weights toward evolving target weights over time (Andonov and Rauh, 2022; Begenau, Liang, and Siriwardane, 2025). The time fixed effects absorb differences in relative returns across asset classes (Parker, Schoar, and Sun, 2023; Harvey, Mazzoleni, and Melone, 2025; Foley-Fisher, Lee, et al., 2025). Both controls for rebalancing significantly affect pension fund flows, but the coefficients on predictable and residual cash flows remain the same.

We further disentangle cash-flow-driven from rebalancing flows by splitting the sample based on the equity versus fixed income performance. The rebalancing hypothesis predicts contrarian trading, so pension funds should not sell equity when fixed income outperforms equity. However, we find that the liquidity-induced sales of equity due to negative cash flows persist irrespective of market conditions. Even in periods when equity underperforms fixed income, a \$1 residual cash outflow leads to \$0.63 equity sales. This relation cannot be reconciled with rebalancing. Overall, negative cash flows have a distinct effect, absorbed mainly through equity sales in both good and bad times.

Our paper contributes to the literature on investment decisions by public US pension funds (e.g., Lucas and Zeldes, 2009; Hochberg and Rauh, 2013; Andonov et al., 2017, 2018; Lu et al., 2019; Begenau et al., 2023). The key innovation of our study is that we do not solely rely on aggregate asset allocation decisions to infer investment decisions. Rather, we obtain an holistic overview of their investment decisions by obtaining 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). However, our paper shows that there are other times during which long-term investors have to sell and act as market destabilizers. Exceptions are Pinter (2023); Pinter et al. (2024); Jansen et al. (2024); 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. Our sample of U.S. public pension funds relies less on derivatives, but we show that liquidity issues arise from other sources, most importantly shocks to pension fund contributions.

Finally, we contribute to the rapidly 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, 2022). 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., 2023; Bretscher et al., 2024; 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, largely because comprehensive data on their holdings have historically been scarce.

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 can 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.[2]

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 U.S. public pension funds largely ignore the lessons of ALM (Novy-Marx and Rauh, 2011), our focus is on how pension funds handle the liquidity demands of their operating cash flows.

[2]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.

Financial theory suggests that an investor's risk-taking should align with its ability to adjust cash flows (spending) to financial market conditions (Campbell and Viceira, 2002; Ang, Papanikolaou, and Westerfield, 2014; Jansen and Werker, 2022). This view implies that pension funds with persistently negative operating cash flows should maintain higher liquidity buffers. Thus, the liquidity buffer hypothesis predicts that pension funds with larger negative cash flows have a higher target allocation to cash and safe fixed income assets, and a lower allocation to illiquid alternatives.[3]

Two strands of literature motivate this hypothesis. First, life-cycle and ALM models suggest that mature pension funds, with benefit outflows that outweigh contribution inflows, should allocate more to safe fixed income assets. Standard life-cycle 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). Even though U.S. public pension funds do not implement ALM models to hedge liabilities, they could rely on these models when designing target allocations. In an ALM setting, equities are long-duration assets, and thus, as pension funds mature, they should reduce the equity share and move to short-term safe assets, which replicate the liabilities (e.g., Sharpe and Tint, 1990; Hoevenaars, Molenaar, Schotman, and Steenkamp, 2008; Jansen, 2025). Second, the payout policy literature argues that mature pension funds are more asset-dependent in their operations and should hold a conservative portfolio (Campbell et al., 2024). Keeping a buffer of liquid and safe 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).

The liquidity buffer hypothesis predicts that pension funds maintain sufficient liquid holdings to absorb negative cash flows. When they face (unexpected) outflows, pension funds follow a pecking

[3]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.

order by selling their 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; Ma, Xiao, and Zeng, 2022; Jansen, Klingler, Ranaldo, and Duijm, 2024). Thus, negative cash flow shocks are absorbed by sales of cash and fixed income, while equities and alternatives remain largely untouched.

An alternative hypothesis is that pension funds, even when facing persistent negative cash flows, have little incentive to maintain a higher target allocation to liquid and safe assets, because cash delivers lower expected returns (Wermers, 2000). Pension funds may perceive that the cost of forgoing higher returns on risky assets outweighs the costs of selling those assets when liquidity needs arise. Under this hypothesis, operating cash flows do 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, despite the differences in liquidity and volatility across assets.

In practice, pro-rata selling may be constrained. Pension funds could rely primarily on equities and fixed income while leaving illiquid alternative assets, such as private equity and real estate, largely untouched. This mechanism predicts that predictable cash-flow-driven sales lead to investment flows that are roughly proportional to the asset class portfolio weights, with adjustments concentrated in fixed income and equity. Importantly, as we show later, because pension funds do not explicitly incorporate cash flows into their target allocations and hold only small amounts of safe assets, negative cash flow *shocks* cannot be absorbed by selling cash or bonds. Given that equities represent the largest fraction of pension portfolios and are relatively more liquid than alternatives, we hypothesize that negative cash flow shocks are absorbed primarily through equity sales.

3 Data on Pension Fund Cash Flows and Assets

Our paper merges several databases 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 FOIA 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 is on a 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 NJ 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.[4]

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.[5] From these sources, we obtain information on pension fund size, cash flows, actual and target asset allocations, performance, and other characteristics.

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

[4]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.

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

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, 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 pension 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 A.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 A.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 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.

Table 1 shows that the predictable *%CF Fit* accounts for the level of negative cash flows. 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.

For both actual and target asset allocations, we follow the data adjustments outlined by Andonov, Bonetti, and Stefanescu (2025) and Begenau, Liang, and Siriwardane (2025) 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 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: FOIA

There is no publicly available dataset on pension fund holdings even though their participants generally 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 Freedom of Information Act (FOIA) 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 150 of them. Out of these responses, 25 pension funds denied our request to deliver data, 4 pension funds demanded a processing fee that we deemed too high[6], and 12 pension funds required citizenship in that state before continuing the process. We thus ended up with 109 pension funds that delivered data to us.

[6]For example, 3 pension funds told us the quarterly data for one year would amount to $5,000, which would imply $120,000 for the full sample period.

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[7]; (iii) the total allocation to different asset classes line up with the PPD database described in Section 3.1. To date, a total of 57 pension satisfy these criteria. We provide a detailed overview of the procedure of making FOIA request in Appendix B.1.

Figure 2 shows the number of pension funds we cover in each period, together with the total assets over time. In 2021, we cover $2.1 trillion in total assets, which corresponds to approximately 40% of the total assets of $5 trillion held by U.S. public pension plans. Appendix Figure B.1 shows the coverage of the FOIA database across states. The key take-away is that we have well-distributed coverage across the nation. Additionally, Table B.1 in the Appendix shows that there is no relationship between pension plans' cash flow and the likelihood of disclosing holdings data through FOIA. The only notable pension fund characteristic that raises the probability of disclosing is pension fund size. The reason is that for paid FOIA requests, we focused on the largest plans. Moreover, we followed up more persistently with large pension plans when initial requests were denied.

Figure 3 shows the detailed cross-sectional average asset allocation of pension funds in our FOIA sample over time. The trends are consistent with those documented in Begenau et al. (2023) and using the PPD database: a rise in the allocation to alternatives from 5% in 2000 to 30% by the end of our sample period, offset by declines in equity and fixed income holdings. Moreover, total liquid asset holdings, defined as cash and U.S. Treasuries, are rather limited, amounting to just under 10%

[7]Several pension funds were exempt from sharing their alternative asset holdings with us.

of total assets over the sample period.

Finally, Table 2 summarizes the FOIA data in greater detail. The first three columns report statistics about the average number of positions that pension funds have in each asset class.[8] On average, pension funds have 3,789 equity positions, while this equals 2,198 for fixed income. The average number of positions is far less in alternative assets, amounting to 260. Turning to the next three columns, we find that pension funds have 2,423 unique positions in equities on average, while this equals 1,820 for fixed income and 192 for alternatives. This suggest that pension funds invest in the same stock across multiple accounts, each exploiting different strategies. Finally, the last three columns show the average allocations to each detailed asset category, confirming the findings of Figure 3.

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 year-month level to address differences in fiscal-year ending dates across pension funds. The year-reporting-month fixed effects capture fluctuations in market returns and macroeconomic conditions.

[8]The procedure to assign asset classes to each individual position is described in detail in Appendix B.1.6.

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 3, 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 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 Flow* 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 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 FOIA holdings data, we can directly examine whether cash flows are related to the composition of cash and fixed income assets. In Table 4, 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.[9] We find that the aggregate cash flows, as well as their predicted component, are not related to the allocation to cash and Treasuries.

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 9% of the pension assets. Pension funds need liquidity not only for benefit payments, but also for capital calls by private equity funds, margin calls on derivatives (e.g., currency risk hedging, commodity investments), etc.

Pension fund could, in principle, address liquidity needs over the short term by using lines of credit. Lines of credit have been used 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 FOIA requests, we find no evidence that pension funds rely on lines of credit to manage cash flows and smooth their liquidity needs. Two factors likely explain why pension funds do not seem to use lines of credit. First, while leverage can smooth transitory shocks, pension funds face structurally predictable negative cash flows that have persisted for the last two decades. Second, issuing debt would increase pension funds' future interest payments, potentially creating more persistent negative cash flows and generating intergenerational wealth transfers from

[9]Online Appendix Table C.4 shows that our results are robust to analyzing separately the holdings of cash and Treasuries, instead of aggregating them.

future to present generations.

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 the investment flows by asset class, we estimate

the following specification:

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

where $Flow_{i,j,t}$ 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 year-month level. The year–reporting–month 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 5, we find that pension funds do not respond to the negative cash flows in line with the liquidity buffer 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 $\text{Pos}_{i,t} = max(\%\text{CF Residual}_{i,t}, 0)$ and %CF Residual $\text{Neg}_{i,t} = min(\%\text{CF Residual}_{i,t}, 0)$ components. Table 5 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 liquidity buffer 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.[10] 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. 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.

Online Appendix Table C.1 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.

The equity outflows in response to negative cash flows necessarily involve selling assets, as dividends are insufficient to cover the balance. First, since most pension funds invest exclusively through external asset managers, dividend payments are typically reinvested automatically rather than distributed to the fund. Second, even if the dividend payments were passed through to the

[10]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 expand significantly an existing mandate.

pension funds, they will not be sufficient to meet the cash needs. For instance, the average %CF Fit is -2.5%, which pension funds absorb by selling 1.36% of equities as a share of the total portfolio ($= 0.025 \times 0.542$). Given that equities represent 50.5% of total assets, this implies selling 2.68% of equity holdings. By comparison, the average dividend yield of S&P 500 firms is 1.87% over 2001–2023 (source: Shiller's data), which falls short of covering predictable outflows. Any residual negative cash flow shocks add further liquidity demands on top of this baseline.

5.1 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 the specifications. The first proxy, the lagged allocation gap, is more specific to the pension fund setting, captures pension funds' gradual adjustments toward evolving target allocations over time (Andonov and Rauh, 2022; Begenau, Liang, and Siriwardane, 2025). 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, Lee, et al., 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 $(\omega_{i,j,t-1}^{Target} - \omega_{i,j,t-1}^{Actual})$, significantly positively predicts flows in the next year in all asset classes. For instance, Column (4) of Table 5 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 year–reporting–month 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 C.3 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 0.09% inflow to cash & fixed income and 0.07% outflow from equities. Importantly, the coefficients on predictable and residual cash flows remain the same.

Finally, Table 6 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 the 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. 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.

5.2 Heterogeneity Across Pension Funds

We argue that pension funds deviate from the pro-rata hypothesis because they maintain low liquidity buffers, forcing them to sell equities when facing negative cash flow shocks. To test this mechanism, we examine heterogeneity across pension funds based on their portfolio composition.

First, we sort funds into terciles 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 have to sell more equities in response to negative cash flow shocks. Table 7 Columns (1) to (4) show that the negative residual cash flows have a different impact on the flows to equity for pension funds in the top and bottom tertiles. For pension funds with high allocation to alternatives, a \$1 residual cash outflows translates into \$0.51 of equity sales, while the effect is insignificant for pension funds with low exposure to alternatives.

Second, Columns (5) to (8) 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. 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.

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 pecking order 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.[11] 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.

For pension funds reporting security-level CUSIP or ISIN numbers, we merge their holdings with public databases to obtain detailed security-level returns. 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.

For stocks with missing ISIN or CUSIP numbers, or 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. 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:

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

where $Flow_{i,j,t}$ is the aggregate quarterly investment flow of pension fund i in year t to security j: $Flow_{i,j,t} = \sum_{q=1}^{4} \frac{A_{i,j,tq} - A_{i,j,tq-1} \times (1+R_{j,tq})}{TA_{i,tq-1}}$. 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 year. In practice, these fixed effects ensure that identification of the interaction between pension fund

[11] 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 C.2 shows that a replication of Table 5 for our FOIA sample renders $\%CF\ Fit$ insignificant across asset classes.

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 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.[12] 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 Table 8 show that following a cash flow shock, pension funds sell equities, consistent with our earlier findings in Table 5. Moreover, pension funds are less likely to sell the most illiquid stocks as measured by the negative interaction term β. Summing up δ and β, we find that pension funds do not buy or sell illiquid stocks when facing cash flow shocks. This result suggests that the equity sales documented in Table 5 is concentrated in liquid stocks. In terms of economic magnitude, we find that a 1% cash flow shock results in additional selling of 0.00023% of each individual stock, or 46% (= 0.00023/0.0005) relative to the average annual flow to each stock. Columns (3) and (4) furthermore show that this effect is primarily driven by positive cash flow shocks. We draw the same conclusion when using MVE as a measure for liquidity instead in Panel B.

[12]We can only determine the Amihud measure of a stock when ISIN or CUSIP numbers are reported. As such, this analysis leaves out pension funds that do not report either ISIN or CUSIP numbers. This leaves us with a cross-section of 42 pension funds.

Turning to pension funds in the top tercile of investments in alternatives, Table 9 shows that these funds sell more equities when facing cash flow shocks, in line with the results in Table 7. In economic terms, Column (2) shows that a 1% cash flow shock leads them to sell 0.0009% of a given stock, compared to 0.0002% for the full sample. Column (4) further shows that they sell less of their illiquid stocks: while a 1% cash flow shock results in sales of 0.0013% of a liquid stock, the magnitude for illiquid stocks is 0.0005% (= 0.00127–0.00074). However, selling 0.0005% of each illiquid stock remains substantial, well above the average stock sales of 0.0002% observed for the full sample. These results indicate that pension funds with high exposure to illiquid alternatives maintain a lower total allocation to equities and need to draw on illiquid stocks when facing cash flow shocks.

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 10 summarizes the results. Focusing on Column (4), we find that pension funds are not more likely to sell U.S. Treasuries when faced with negative cash flow shocks. This finding is consistent with the earlier results in Table 4 and shows that pension funds do not draw on their fixed income, or Treasury portfolios, when faced with negative cash flow shocks.

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 liquid buffers. Funds absorb predictable outflows through pro-rata sales tilted towards

fixed income and equities, while negative cash flow shocks lead mainly to equity sales. Within equities, pension funds absorb negative cash flow shocks through a mix of pro-rata selling and a liquid-assets-first strategy: they sell their most illiquid stocks less, but funds with high allocations to illiquid alternatives are forced to draw more heavily on their illiquid equity holdings.

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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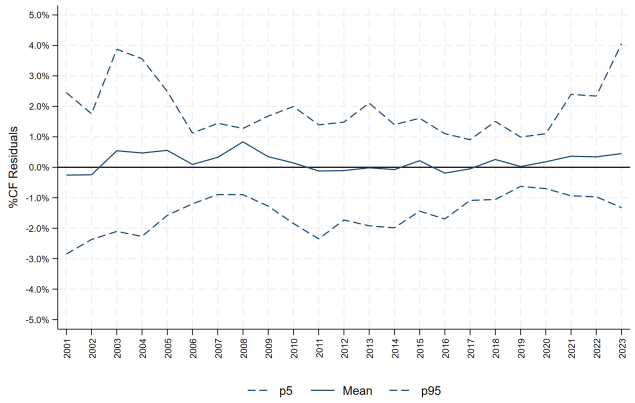
Figure 1: Pension Fund Cash Flows

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.

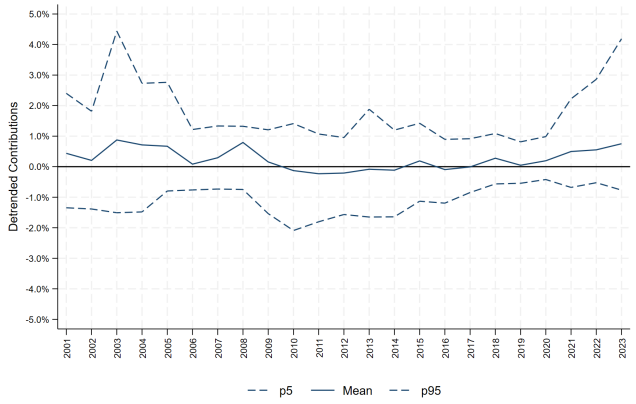
Panel A: Net Operating Cash Flows



Panel B: Detrended Residual Cash Flows



Panel C: Detrended Contributions



Panel D: Detrended Benefits

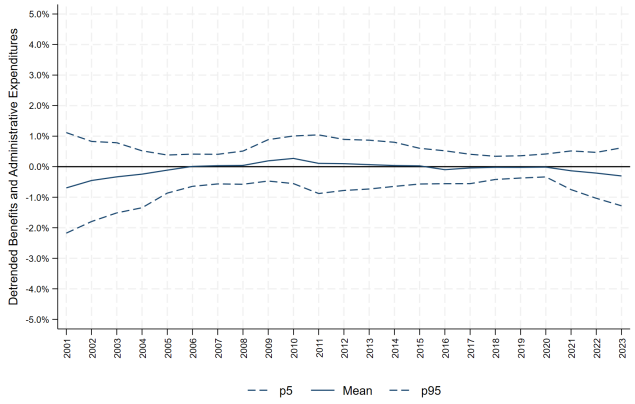


Figure 2: Pension Fund Holdings Data Coverage

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.

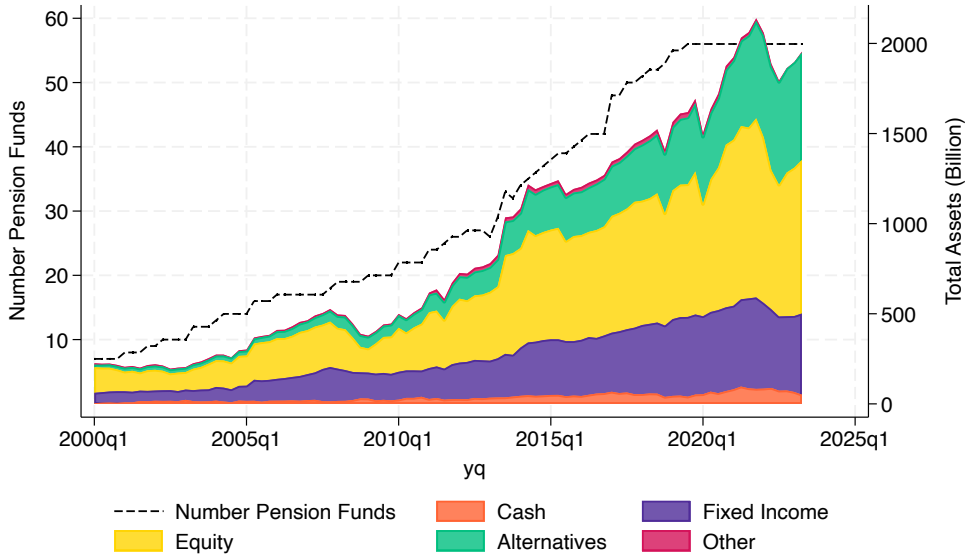


Figure 3: Pension Fund Holdings Data Detailed Asset Allocation

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: FOIA.

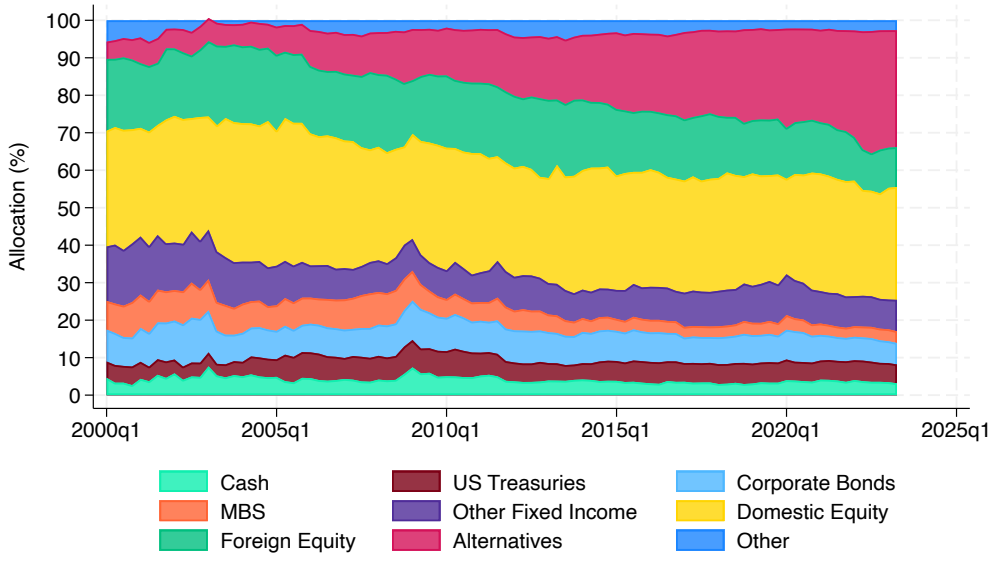


Table 1: Pension Fund Summary Statistics

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 FOIA subsample of pension funds that disclose holdings data.

	Full Sample				FOIA Subsample			
	N	Mean	Median	SD	N	Mean	Median	SD
Panel A: Cash Flows								
%CF	4,083	-2.4	-2.3	3.3	728	-2.2	-2.0	2.7
%CF Fit	4,083	-2.5	-2.4	2.2	728	-2.4	-2.0	2.0
%CF Residuals	4,083	0.2	-0.0	2.8	728	0.2	-0.0	2.3
%CF Predicted	2,222	-2.8	-2.5	2.6	573	-2.5	-2.1	2.4
%CF Shock	2,222	0.1	-0.0	1.8	573	0.2	-0.0	1.7
Panel B: Pension Fund Characteristics								
Pension Fund AUM ($ bil)	4,083	18.3	5.0	36.5	728	29.4	11.0	54.9
GASB Funding Status	4,035	78.0	78.3	16.8	727	76.8	77.5	16.2
Return	4,083	6.5	8.1	10.9	728	7.4	8.0	10.4
Panel C: Target Asset Allocation								
%Cash & FI	3,496	25.9	25.7	7.1	692	25.2	25.0	7.0
%Cash	3,496	0.3	0.0	2.4	692	0.5	0.0	1.7
%Fixed Income	3,496	25.6	25.0	7.4	692	24.7	25.0	7.0
%Risky	3,496	74.1	74.3	7.1	692	74.8	75.0	7.0
%Equity	3,496	50.5	51.0	10.6	692	48.5	48.0	11.3
%Alternatives	3,496	23.6	23.4	13.1	692	26.3	26.6	13.3
%Private Equity	3,496	6.9	6.9	6.0	692	7.7	8.0	6.5
%Real Assets	3,496	9.9	10.0	6.1	692	10.5	11.0	5.9
%Hedge Funds	3,496	4.9	0.0	6.7	692	6.0	4.0	7.1
%Other Alternatives	3,496	1.8	0.0	5.3	692	2.2	0.0	6.2

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 FOIA 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	SD	Median	Mean	SD	Median	Mean	SD	Median
Cash	148	48	380	23	8	46	3.9	2.8	3.8
Fixed Income									
Corporate Bonds	1148	667	1237	901	600	1024	7.7	7.0	4.9
US Treasuries	215	83	289	150	68	206	5.6	3.9	5.4
MBS	661	262	1011	630	251	1001	4.3	3.8	3.4
Other Fixed Income	174	92	241	139	71	174	9.2	8.1	7.3
Equity									
Equity Domestic	2063	1201	2619	1354	854	1415	30.5	31.0	13.3
Equity Foreign	1726	668	3107	1069	528	1574	15.9	16.7	10.8
Alternatives									
Private Equity	81	30	115	77	25	109	9.9	7.4	10.0
Real Estate	145	60	257	89	48	118	5.5	5.7	3.9
Other	34	8	75	26	5	58	4.8	0.4	7.3

Table 3: 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 year-reporting-month 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
Year-Reporting-Month 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
Year-Reporting-Month 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
Year-Reporting-Month 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
Year-Reporting-Month 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 4: 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 FOIA 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 pension fund and year-reporting-month fixed effects. We cluster standard errors by pension fund, and report standard errors in brackets. $^{*}p < .10$; $^{**}p < .05$; $^{***}p < .01$.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Mean Dep. Var.	0.092	0.092	0.092	0.092	0.088	0.088	0.088	0.088
%CF	-0.205	0.112						
	[0.260]	[0.123]						
%CF Fit			-0.722	-0.071				
			[0.386]	[0.664]				
%CF Predicted					-0.412	-0.165		
					[0.293]	[0.193]		
%CF Volatility							0.113	-0.132
							[0.212]	[0.190]
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pension Fund FE		Yes		Yes		Yes		Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	738	738	738	738	601	601	601	601
R-squared	0.076	0.677	0.112	0.676	0.063	0.749	0.042	0.749

Table 5: 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 year-reporting-month 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
Year-Reporting-Month 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 6: 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 $(\omega_{i,j,t-1}^{Target} - \omega_{i,j,t-1}^{Actual})$ of pension fund i in asset class j in year $t-1$. The specifications include pension fund and year-reporting-month 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 $R_{EQ,t}^{BM} > R_{FI,t}^{BM}$						
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
Year-Reporting-Month 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 $R_{EQ,t}^{BM} < R_{FI,t}^{BM}$						
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
Year-Reporting-Month 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 7: Equity 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 in 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 in equity. The specifications include pension fund and year-reporting-month 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)
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
Year-Reporting-Month 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

Table 8: Equity Security Flows and Cash Flows– Full Sample

In this table, observations are at the pension-fund-stock-year level. The dependent variable measures the investment flow (in basis points) of pension fund i in stock j in 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 $A_{i,j,tq}$ is the dollar amount of assets invested by pension fund i in stock j in quarter q of year t, $R_{j,tq}$ 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 control for the lagged log of pension fund size, lagged GASB funding ratio, and lagged allocation gap, which captures the difference between the actual and target asset allocation $(\omega_{i,j,t}^{Target} - \omega_{i,j,t}^{Actual})$. 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 security, and report standard errors in brackets. $^*p < .10$; $^{**}p < .05$; $^{***}p < .01$.

Panel A: Amihud Measure				
	(1)	(2)	(3)	(4)
Mean Dep. Var.	0.048	0.050	0.048	0.050
%CF Residuals	0.015***	0.023***		
	[0.003]	[0.004]		
%CF Residuals Pos			0.013***	0.021***
			[0.004]	[0.005]
%CF Residuals Neg			0.029***	0.041***
			[0.007]	[0.011]
%CF Residuals × Amihud High	-0.017***	-0.024**		
	[0.003]	[0.008]		
%CF Residuals Pos × Amihud High			-0.024***	-0.032***
			[0.004]	[0.006]
%CF Residuals Neg × Amihud High			0.020*	0.021
			[0.009]	[0.039]
Amihud High	0.003		0.013**	
	[0.004]		[0.005]	
Controls	Yes	Yes	Yes	Yes
Pension Fund FE	Yes	Yes	Yes	Yes
Year FE	Yes		Yes	
Security-Year FE		Yes		Yes
Observations	889,175	693,360	889,175	693,360
R-squared	0.004	0.383	0.004	0.383
Panel B: Market Value Equity (MVE)				
	(1)	(2)	(3)	(4)
Mean Dep. Var.	0.048	0.050	0.048	0.050
%CF Residuals	0.016***	0.023***		
	[0.003]	[0.004]		
%CF Residuals Pos			0.014***	0.021***
			[0.004]	[0.005]
%CF Residuals Neg			0.028***	0.039***
			[0.007]	[0.011]
%CF Residuals × MVE Low	-0.018***	-0.027***		
	[0.004]	[0.008]		
%CF Residuals Pos × MVE Low			-0.026***	-0.036***
			[0.004]	[0.005]
%CF Residuals Neg × MVE Low			0.034*	0.033
			[0.016]	[0.041]
MVE Low	0.017		0.031*	
	[0.009]		[0.012]	
Controls	Yes	Yes	Yes	Yes
Pension Fund FE	Yes	Yes	Yes	Yes
Year FE	Yes		Yes	
Security-Year FE		Yes		Yes
Observations	894,029	696,912	894,029	696,912
R-squared	0.004	0.383	0.004	0.383

Table 9: Equity Security Flows and Cash Flows– Top Tercile Alternatives

In this table, observations are at the pension-fund-stock-year level, for pension funds in the top tercile of asset allocation to alternatives. The dependent variable measures the investment flow (in basis points) of pension fund i in stock j in 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 $A_{i,j,tq}$ is the dollar amount of assets invested by pension fund i in stock j in quarter q of year t, $R_{j,tq}$ 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 control for the lagged log of pension fund size, lagged GASB funding ratio, and lagged allocation gap, which captures the difference between the actual and target asset allocation ($\omega_{i,j,t}^{Target} - \omega_{i,j,t}^{Actual}$). 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. MVE Low are stocks in the bottom tercile of total market cap. The specifications include fixed effects as reported. We cluster standard errors by security, and report standard errors in brackets. $^{*}p < .10$; $^{**}p < .05$; $^{***}p < .01$.

Panel A: Amihud Measure				
	(1)	(2)	(3)	(4)
Mean Dep. Var.	0.009	-0.003	0.009	-0.003
%CF Residuals	0.064***	0.092***		
	[0.006]	[0.010]		
%CF Residuals Pos			-0.009	-0.036**
			[0.011]	[0.012]
%CF Residuals Neg			0.079***	0.127***
			[0.008]	[0.013]
%CF Residuals × Amihud High	-0.015**	-0.042***		
	[0.005]	[0.008]		
%CF Residuals Pos × Amihud High			0.009*	0.043***
			[0.004]	[0.008]
%CF Residuals Neg × Amihud High			-0.019	-0.074***
			[0.013]	[0.016]
Amihud High	0.033***		0.027***	
	[0.003]		[0.005]	
Controls	Yes	Yes	Yes	Yes
Pension Fund FE	Yes	Yes	Yes	Yes
Year FE	Yes		Yes	
Security-Year FE		Yes		Yes
Observations	387,962	290,685	387,962	290,685
R-squared	0.021	0.309	0.021	0.309
Panel B: Market Value Equity (MVE)				
	(1)	(2)	(3)	(4)
Mean Dep. Var.	0.009	-0.004	0.009	-0.004
%CF Residuals	0.064***	0.091***		
	[0.006]	[0.010]		
%CF Residuals Pos			-0.006	-0.034**
			[0.011]	[0.012]
%CF Residuals Neg			0.079***	0.126***
			[0.008]	[0.013]
%CF Residuals × MVE Low	-0.019***	-0.038***		
	[0.005]	[0.007]		
%CF Residuals Pos × MVE Low			0.004	0.034***
			[0.003]	[0.008]
%CF Residuals Neg × MVE Low			-0.025*	-0.060***
			[0.013]	[0.016]
MVE Low	0.035***		0.028***	
	[0.003]		[0.004]	
Controls	Yes	Yes	Yes	Yes
Pension Fund FE	Yes	Yes	Yes	Yes
Year FE	Yes		Yes	
Security-Year FE		Yes		Yes
Observations	390,695	292,192	390,695	292,192
R-squared	0.021	0.309	0.021	0.310

Table 10: Fixed Income Security Flows and Cash Flows

In this table, observations are at the pension-fund-stock-year level. The dependent variable measures the investment flow (in basis points) of pension fund i in bond j in 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 $A_{i,j,tq}$ is the dollar amount of assets invested by pension fund i in bond j in quarter q of year t, $R_{j,tq}$ 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 control for the lagged log of pension fund size, lagged GASB funding ratio, and lagged allocation gap, which captures the difference between the actual and target asset allocation ($\omega_{i,j,t}^{Target} - \omega_{i,j,t}^{Actual}$). 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 security, and report standard errors in brackets. *$p < .10$; **$p < .05$; ***$p < .01$.

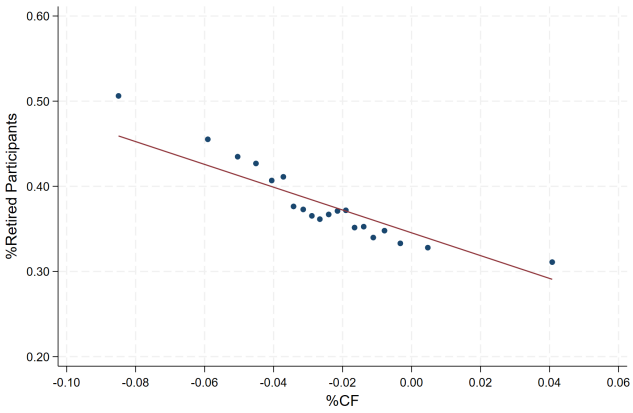
	(1)	(2)	(3)	(4)
Mean Dep. Var.	-0.093	-0.091	-0.093	-0.091
%CF Residuals	0.0009	0.0026*		
	[0.0010]	[0.0013]		
%CF Residuals Pos			0.0052***	0.0060***
			[0.0010]	[0.0013]
%CF Residuals Neg			-0.0145***	-0.0074*
			[0.0025]	[0.0035]
%CF Residuals × U.S. Treasuries	0.0146	-0.0012		
	[0.0110]	[0.0183]		
%CF Residuals Pos × U.S. Treasuries			0.0035	0.0048
			[0.0115]	[0.0164]
%CF Residuals Neg × U.S. Treasuries			0.0812**	-0.0442
			[0.0314]	[0.0632]
U.S. Treasuries	-0.3178***		-0.2978***	
	[0.0135]		[0.0160]	
Controls	Yes	Yes	Yes	Yes
Pension Fund FE	Yes	Yes	Yes	Yes
Year FE	Yes		Yes	
Security-Year FE		Yes		Yes
Observations	3,295,669	1,490,926	3,295,669	1,490,926
R-squared	0.029	0.341	0.029	0.341

Online Appendix A: Cash Flow Measures

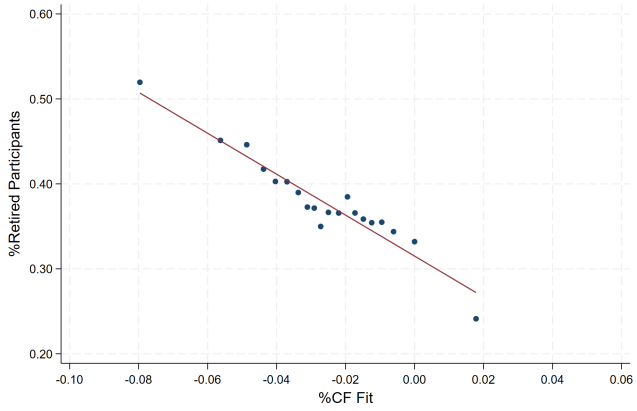
Figure A.1: Pension Fund Cash Flows and the Percentage of Retired Participants

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.

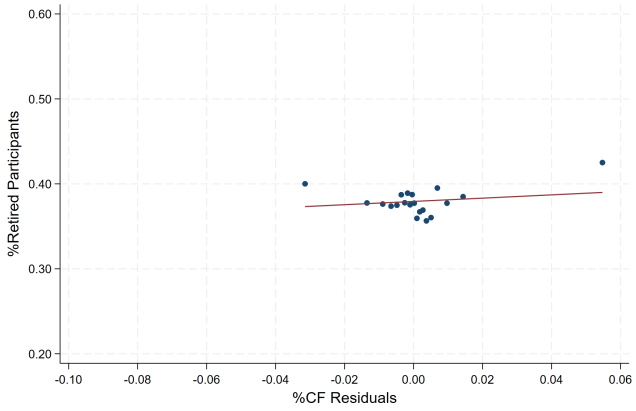
Panel A: Net Operating Cash Flows



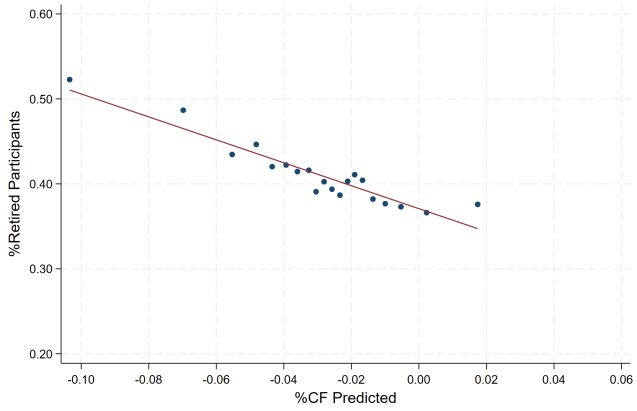
Panel B: Fitted Cash Flows



Panel C: Residual Cash Flows



Panel D: Predicted Cash Flows



Panel E: Cash Flow Shocks

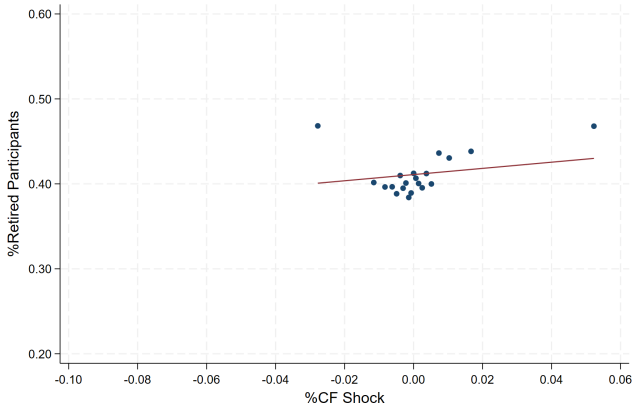


Table A.1: Correlations of Cash Flow Measures

	%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

Online Appendix B: FOIA Requests of Pension Fund Holdings

B.1 FOIA 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).

B.1.1 Data Requested

In each public disclosure request, 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.
3. Data delivered in Excel format, when possible.

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

B.1.2 Submission Procedure

The submission procedure of making FOIA requests proceeds as follows:

1. Locate the pension fund's FOIA submission instructions by searching its website for "Public Records Request," "FOIA," or "Data Request."
2. Submit the request through either an online portal or email, depending on the pension fund's preferred method.
3. Each submission includes:
   (a) A formal letter detailing the project and specifying the requested data.
   (b) A sample spreadsheet that illustrates the preferred format.

B.1.3 Response Summary

Below, we summarize the outcomes of the FOIA requests, including response rates, delivery times, and common barriers to data access:

1. Total FOIA requests submitted: 176 pension funds
2. Average time to initial response: 27 days
3. Average time to data delivery: 88 days
4. No response received: 27 cases
5. Denials received: 23 cases
6. Citizenship requirement cited: 12 cases
7. Fee requirement cited: 14 cases
8. Excel-formatted data received: 82 responses
9. PDF reports received (no spreadsheets): 19 responses

B.1.4 Data Verification and Processing

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

1. Initial Cleaning
   (a) Excel files are cleaned and processed in Stata.
   (b) PDF files are parsed using Python and subsequently cleaned in Stata.
   (c) Core variables include: Preqin ID, Pension Fund Name, Quarter, Security Name, Security Description, Market Value (base/local), Price (base/local), Shares, Asset Class, Sub-Asset Class, ISIN/CUSIP/SEDOL/Bloomberg Ticker, Currency, Country, Account Name, Maturity Date, Coupon Rate, and Yield to Maturity.
2. Cross-Validation FOIA Data
   (a) Aggregate market values in FOIA 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 FOIA data.
      ii. PPD coverage limited to defined benefit plans, while FOIA data encompass broader plans, such as defined contribution or OPEB/Healthcare Trusts.
3. Follow-Up Requests
   (a) Pension funds are contacted to clarify discrepancies or provide missing data.
   (b) For complex issues, virtual meetings are offered to explain the research needs and improve data provision outcomes.

B.1.5 Final Cleaning

To construct the final sample used in our empirical analysis, we apply a set of selection criteria to the processed FOIA 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 57 pension funds. Figure B.1 lays out the coverage of the sample by state.

B.1.6 Asset Classification

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
2. Fixed Income
    (a) Corporate Bonds
    (b) Government Bonds
    (c) Municipal Bonds
    (d) Mortgage-Backed Securities
    (e) Other Fixed Income
3. Cash
4. Repo
5. Mutual Funds
    (a) Equity Funds
    (b) Fixed Income Funds
    (c) Other Funds
6. Alternatives
    (a) Private Equity
    (b) Real Estate
    (c) Other
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 entirely 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.

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

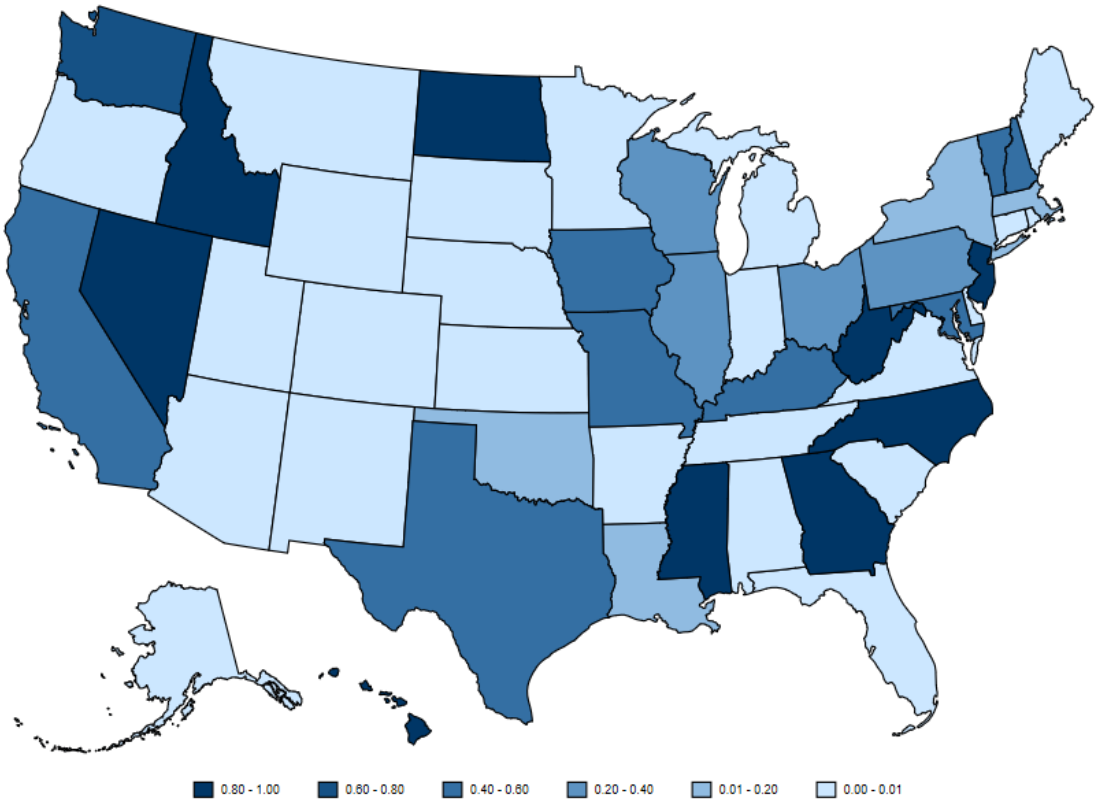


Table B.1: Probability of Pension Funds Disclosing Holdings Data

In this table, observations are at the pension-fund-year level. Logit regressions, we present marginal effects at the means. 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. = 19.8%)						
	(1)	(2)	(3)	(4)	(5)	(6)
%CF	0.660	-0.292				
	[0.486]	[0.798]				
%CF Fit			1.595	-1.384	1.586	-1.391
			[1.199]	[1.712]	[1.196]	[1.707]
%CF Residuals			0.319	0.087		
			[0.260]	[0.256]		
%CF Residuals Pos					0.272	0.073
					[0.285]	[0.255]
%CF Residuals Neg					0.745	0.210
					[1.896]	[1.535]
Pension Fund Size	0.056***	0.100***	0.056***	0.102***	0.056***	0.102***
	[0.017]	[0.031]	[0.017]	[0.031]	[0.017]	[0.031]
GASB Funding Status	0.068	-0.084	0.040	-0.062	0.036	-0.063
	[0.136]	[0.213]	[0.137]	[0.215]	[0.137]	[0.215]
Return	-0.075	0.305	-0.059	0.291	-0.057	0.292
	[0.333]	[0.385]	[0.332]	[0.379]	[0.335]	[0.382]
%Equity	-0.090	0.042	-0.061	0.011	-0.061	0.010
	[0.328]	[0.414]	[0.338]	[0.406]	[0.338]	[0.407]
%Real Assets	-0.304	-0.315	-0.302	-0.292	-0.305	-0.293
	[0.414]	[0.467]	[0.411]	[0.465]	[0.410]	[0.465]
%Hedge Funds	0.158	0.451	0.171	0.421	0.172	0.421
	[0.371]	[0.534]	[0.373]	[0.533]	[0.374]	[0.534]
%Private Equity	-0.427	-0.544	-0.429	-0.556	-0.428	-0.556
	[0.404]	[0.517]	[0.406]	[0.515]	[0.406]	[0.515]
%Other Alternatives	-0.001	0.612	-0.010	0.628	-0.012	0.628
	[0.443]	[0.545]	[0.437]	[0.549]	[0.436]	[0.549]
Year-Reporting-Month FE	Yes	Yes	Yes	Yes	Yes	Yes
State FE		Yes		Yes		Yes
Observations	3,251	2,375	3,251	2,375	3,251	2,375

Online Appendix C: Pension Fund Aggregate Flows

Table C.1: Asset Class Investment Flows and Cash Flows - Alternative CF Decomposition

Robustness test of Table 5: 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 year-reporting-month 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
Year-Reporting-Month 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 C.2: Asset Class Investment Flows and Cash Flows - FOIA Subsample

Robustness test of Table 5: We replicate the analysis for the FOIA 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 year-reporting-month 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	-0.025	-0.025	-0.001	-0.001
%CF Fit	0.249	0.289	-0.013	-0.005	0.229	0.170
	[0.218]	[0.209]	[0.330]	[0.334]	[0.327]	[0.335]
%CF Residuals	0.151		0.535***		0.277***	
	[0.101]		[0.085]		[0.101]	
%CF Residuals Pos		0.297***		0.578***		0.096
		[0.089]		[0.106]		[0.107]
%CF Residuals Neg		-0.260***		0.412***		0.789***
		[0.087]		[0.107]		[0.088]
Allocation Gap	0.237**	0.243**	0.335***	0.338***	0.242***	0.255***
	[0.102]	[0.105]	[0.056]	[0.056]	[0.044]	[0.042]
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Pension Fund FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-Reporting-Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	660	660	660	660	656	656
R-squared	0.286	0.297	0.371	0.371	0.357	0.369
p-value test		0.00		0.32		0.00

Table C.3: Asset Class Investment Flows and Cash Flows - Rebalancing Flows

Robustness test of Table 5: We control for the difference in returns between equities and fixed income ($R^{BM}_{EQ,t} - R^{BM}_{FI,t}$) instead of including year-reporting-month 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 $\text{Pos}_{i,t} = max(\%\text{CF Residual}_{i,t}, 0)$ 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 ($\omega^{Target}_{i,j,t-1} - \omega^{Actual}_{i,j,t-1}$) 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

Online Appendix D: Extra Results Pension Fund Holdings Data

Table C.4: 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 either cash (Panel A) or U.S. Treasury securities (Panel B) based on the holdings data obtained through FOIA 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 pension fund and year-reporting-month fixed effects. We cluster standard errors by pension fund, and report standard errors in brackets. $*p < .10$; $**p < .05$; $***p < .01$.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Allocation to Cash								
Mean Dep. Var.	0.0373	0.0373	0.0373	0.0373	0.035	0.035	0.035	0.035
%CF	0.041	0.136						
	[0.159]	[0.129]						
%CF Fit			-0.156	-0.261				
			[0.246]	[0.333]				
%CF Predicted					0.013	-0.142		
					[0.137]	[0.141]		
%CF Volatility							0.307	-0.021
							[0.194]	[0.077]
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pension Fund FE		Yes		Yes		Yes		Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	738	738	738	738	601	601	601	601
R-squared	0.036	0.679	0.041	0.676	0.026	0.724	0.041	0.722
Panel B: Allocation to U.S. Treasuries								
Mean Dep. Var.	0.054	0.054	0.054	0.054	0.053	0.053	0.053	0.053
%CF	-0.246	-0.023						
	[0.242]	[0.091]						
%CF Fit			-0.566	0.190				
			[0.424]	[0.550]				
%CF Predicted					-0.425	-0.023		
					[0.316]	[0.111]		
%CF Volatility							-0.194	-0.111
							[0.198]	[0.142]
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pension Fund FE		Yes		Yes		Yes		Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	738	738	738	738	601	601	601	601
R-squared	0.072	0.721	0.092	0.721	0.076	0.827	0.052	0.827