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 both fixed income and equities, but they meet negative cash flow shocks primarily by liquidating equities. At the security level, pension funds sell across equities and do not follow a liquid-assets-first approach. Pension funds more exposed to alternatives rely disproportionately on equity sales to meet liquidity needs. These liquidity-driven equity sales occur even during periods of negative equity returns, which confirms that liquidity sales are separate from portfolio rebalancing. Our findings thus reject the view of pension funds as liquidity providers in financial markets.

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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 who can act as liquidity providers in financial markets by absorbing supply shocks and purchasing assets when other market participants are forced to sell (e.g., Greenwood and Vayanos, 2014; Timmer, 2018).

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. This cash flow shortfall implies that pension funds need to liquidate part of their portfolio to meet obligations. Such entities 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 59 pension funds that cover approximately 47% 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 at a more granular level when facing cash flow shocks.

Pension fund net operating cash flows are defined as the difference between contribution inflows and 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 that arise due to sudden shifts in benefit payouts or contribution inflows.

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 spending 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 hypothesis implies that pension funds with larger negative cash flows should have a higher target allocation to cash and safe fixed income, and a lower allocation to illiquid alternatives.

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

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

We first examine whether pension funds incorporate differences in operating cash flows in their target asset allocations. Our 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 lower 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 the allocation to cash and U.S. Treasuries directly, 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 10% 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 the ways predicted by our 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 funds' responses to unpredictable cash flows are asymmetric and deviate again from our hypothesis. 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. Strikingly, this pattern—selling mostly equities while leaving cash and fixed income untouched in response to negative cash flow shocks—reflects more equity selling than either our hypothesis or the alternative pro-rata hypothesis would predict.

We argue that pension funds deviate from pro-rata selling when facing negative shocks because they hold only low liquidity buffers, forcing them to sell equities. The 10% of pension fund assets in cash and U.S. Treasuries could 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. Examining whether pension funds sell fewer illiquid stocks when faced with cash flow shocks allows us to test our hypothesis *within* equities. We define illiquid stocks as those in the top tercile of the Amihud illiquidity measure (Amihud, 2002) or the bottom tercile of market capitalization.

We find that pension funds do not disproportionately sell fewer illiquid stocks when faced with negative cash flow shocks, inconsistent with our hypothesis but consistent with pro-rata flows within equities. Using fixed income holdings data, we also confirm that pension funds leave U.S. Treasuries untouched when meeting liquidity needs. Taken together, these patterns imply that pension funds

[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.

rely on both liquid and illiquid equity sales to meet cash needs, likely incurring nontrivial transaction costs.

Our main cash flow measure focuses on operating cash flows and excludes income from investment activities such as dividends and interest. This definition better reflects the cash flows that pension funds experience, as most funds invest through external asset managers under contracts that reinvest dividends and interest rather than distributing them, so funds must submit redemption requests to meet cash flow needs. Although investment income can provide cash without requiring transactions, it is insufficient to cover the liquidity needs. Even when we add investment income, the combined operating and investment cash flows turn negative after 2008 and fluctuate around -1% of assets. Any residual negative cash flow shocks generate additional liquidity demands. In robustness tests, controlling for investment income does not affect the relation between cash flow shocks and asset sales: negative residual cash outflows result in sales of equities and alternatives. Using the FOIA holdings data, we also confirm that pension funds with larger cash flow needs do not select securities with higher investment income, i.e., higher-paying dividend stocks or higher-paying coupon bonds.

The liquidity-driven flows induced by negative cash flows differ significantly from rebalancing flows driven by market movements. To separate rebalancing flows, we control for the lagged allocation gap and time fixed effects. The allocation gap captures pension funds' gradual adjustments of actual allocation weights toward evolving target weights 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 and Lee, 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 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. Moreover, we show that after the Global Financial Crisis, pension funds sold equities in every quarter with negative stock market returns. Taken together, negative cash flows have a distinct effect, absorbed mainly through equity sales in both good and bad times.

Overall, our findings provide convincing evidence that pension funds are predictable net sellers in equity markets. This rejects the view of pension funds as long-horizon investors insulated from short-term market fluctuations, as they sell equities even when equities underperform relative to other asset classes.

Our paper contributes to the literature on investment decisions by public U.S. public pension funds (e.g., Lucas and Zeldes, 2009; Hochberg and Rauh, 2013; Andonov et al., 2017; Lu et al., 2019; Begenau et al., 2023). The key innovation of our study is that we focus on their operating cash flows and examine how pension fund manage their liquidity needs. Our analysis does not solely rely on aggregate asset allocations. Rather, we obtain an holistic overview of their investment decisions with security-level data on all asset classes, including equities, fixed income, cash, alternative assets, and derivatives.

Our paper also contributes to the literature that shows long-term investors act as stabilizers in financial markets, because they do not have to sell in times of crises (e.g., Timmer, 2018; Chodorow-Reich et al., 2021; Coppola, 2025; Zhou, 2024). 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. We show that U.S. public pension funds rely substantially less on derivatives, but we find that liquidity issues arise from other sources, most importantly shocks to pension fund contributions in the presence of large allocations to alternative assets and low liquidity buffers.

Finally, we contribute to the growing demand-based asset pricing literature which studies the equilibrium relation between prices and holdings or flows (e.g., Koijen and Yogo, 2019; Gabaix and Koijen, 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 changes in financial market conditions (Campbell and Viceira, 2002; Ang, Papanikolaou, and Westerfield, 2014; Jansen and Werker, 2022). This view implies that pension funds with larger negative cash flows or a higher volatility of cash flows should have a higher target allocation to cash and safe fixed income assets, and a lower allocation to illiquid alternatives.[3]

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

Two strands of the literature, specific to pension funds, further 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 regularly commission asset-liability studies to design 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 spending 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).

[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.

Hypothesis 2(a). *In response to predictable cash outflows, pension funds draw down on their liquidity buffers.*

Following directly on Hypothesis 1, the implication is that predictable cash outflows should be met using the assets that pension funds are already holding to meet cash flows. Pension funds facing predictable outflows should therefore meet those outflows primarily by drawing down their liquidity buffers, i.e., cash and safe fixed income assets.

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

When a pension fund faces unpredictable cash flow shocks, they should liquidate their most liquid assets first and turn to riskier and illiquid assets only if shocks exceed available buffers. Thus, pension funds follow a liquid-asset-first approach by selling their 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), while equities and alternatives remain largely untouched. This strategy minimizes price impact and trading costs.

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

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

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. This trade-off is reinforced by the institutional and political context of public pension fund accounting. Under GASB guidelines, pension funds discount their liabilities using the expected rate of return, which directly affects reported funding status. Consequently, pension fund boards, which are often composed of political appointees and employee representatives, set high expected returns (e.g., Novy-Marx and Rauh, 2011; Andonov, Bauer, and Cremers, 2017), and pension CIOs are tasked with designing portfolios that could meet them. The resulting incentive structure discourages holding low-yielding liquid and safe assets. Under this hypothesis, operating cash flows 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.

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

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 59 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, the FOIA subsample covered \$2.4 trillion in total assets, which corresponds to approximately 47% of the total assets of \$5.1 trillion held by U.S. public pension plans. Appendix Figure B.1 shows that the coverage of the FOIA database is well-distributed across states. Additionally, Appendix Table B.1 shows that there is no relationship between pension fund cash flows and the likelihood of disclosing holdings data through FOIA. The only notable pension fund characteristic that raises the probability of disclosure is pension fund size, while the holdings disclosure is unrelated to pension funding status, performance, and asset allocation.

Figure 3 shows the detailed cross-sectional average asset allocation of pension funds in our FOIA sample over time. The trends in the holdings data are consistent with those observed in the aggregate pension data and documented in prior research (e.g., Andonov and Rauh, 2022; Begenau, Liang, and Siriwardane, 2023): 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, the holdings data enable us to document that the total liquid asset holdings, defined as cash and U.S. Treasuries, are rather limited, amounting to just under 10% of total assets.

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

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 4,075 equity positions, while this equals 2,304 for fixed income. The average number of positions is lower in alternative assets, amounting to 269.[9] Turning to the next three columns, we find that pension funds have 2,583 unique positions in equities on average, while this equals 2,009 for fixed income and 193 for alternatives. This suggest that pension funds invest in the same stock across multiple accounts, each exploiting different strategies. The last three columns show the allocations to each detailed asset category, confirming the findings of Figure 3.

Finally, Table 3 summarizes the derivatives data obtained through FOIA requests. Derivative usage is heterogeneous across pension funds; for instance, only 53% of the sample uses equity futures, while 64% uses fixed income instruments (including futures, forwards, and swaps), and 38% uses currency forwards or swaps. However, despite this heterogeneity, the economic magnitude of these positions is relatively small. Total gross notional amounts (which reflect the maximum potential exposure since long and short positions do not offset) are limited. For example, the gross notional in equity futures is only 0.1% of total assets on average, and 0% for the median fund.[10] Derivative usage is more substantial within fixed income, with the total gross notional equaling 2.4% of total assets, while for currency derivatives, it is 0.1%. Although a large fraction of the sample uses options (72.9%), this usage represents only 0.5% of total assets.

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

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

[10] We exclude 15 pension funds that do not report the currency in which the notional amount is denominated to ensure accurate conversion to USD and allow for a consistent comparison.

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. In the models, we either examine cross-sectional variation or include pension fund fixed effects (PF_i) to explore within-fund variation. We cluster the standard errors by pension fund.

In Table 4, we find no relation between cash flows and target allocations. The liquidity buffer hypothesis predicts a negative relation between $\%CF$ and allocation to cash & FI. Contrary to this hypothesis, Columns (1) and (2) of Panel A show that the variation in $\%CF$ across and within pension funds is not related to the target allocation to cash & FI. In addition, Columns (5) and (6) show that pension funds with lower cash flows do not have a lower allocation to illiquid alternatives.

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

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

While the 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 5, the dependent variables capture actual allocations to cash and U.S. Treasuries, which are the least volatile and most liquid parts of the pension portfolio.[11] 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

[11] Online Appendix Table C.6 shows that our results are robust to analyzing separately the holdings of cash and Treasuries, instead of aggregating them.

in general maintain low liquidity buffers: cash and Treasuries together account for 10% 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 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 investment flows by asset class, we estimate the following specification:

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

where $Flow_{i,t}$ is the investment flow of pension fund i in year t to cash & fixed income, equity, or alternative assets. $CF_{i,t}$ captures the cash flows. We focus mainly on fitted and residual cash flows in the models. $X_{i,t-1}$ is a vector of lagged controls that includes the log of pension fund size, GASB funding status, and allocation gap. The lagged allocation gap, defined as $(\omega^{Target}_{i,j,t-1} - \omega^{Actual}_{i,j,t-1})$, 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 6, we find that pension funds do not respond to the negative cash flows in line with the liquid-asset-first hypothesis as the flows are not highly concentrated in cash and fixed income. To the predictable cash flow component (*%CF Fit*), pension funds respond with constrained pro-rata flows. Based on Columns (1) and (3), $1 of predictable cash outflows is absorbed by selling $0.35 of cash & FI, and $0.54 of equities. These amounts are close to the average target weights to these asset classes presented in Table 1. The flows to alternatives are positive, but statistically insignificant, which confirms that the pro-rata selling is constrained as fixed income and equity assets absorb a slightly larger share of the flows. Overall, predictable cash (out)flows do not induce significant shifts in major asset class weights and do not make pension fund portfolios relatively riskier.

We examine how pension funds adjust to unpredictable cash flows by implementing a piecewise decomposition of the *%CF Residuals* variable into $\%CF\ Residual\ Pos_{i,t} = \max(\%CF\ Residual_{i,t}, 0)$ and $\%CF\ Residual\ Neg_{i,t} = \min(\%CF\ Residual_{i,t}, 0)$ components. Table 6 shows that pension funds respond asymmetrically to positive and negative cash flows. Their investment flows in response to residual cash flows deviate from both the liquid-asset-first hypothesis and pro-rata selling. Positive residual cash inflows are absorbed mainly by cash and fixed income ($0.78 per $1), with only $0.22 going to equities and $0.04 to alternatives.[12] 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

[12]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.

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. We also replicate the analysis for the FOIA subsample of pension funds in Online Appendix Table C.2 and show that our results remain the same.

5.1 Negative Cash Flows and Investment Income

Our main measure only considers the net cash flows from pension fund operations, and does not incorporate the cash flows from investment activity, such as income from dividends and interest payments. This definition of the main cash flow measure better reflects the flows that pension funds experience because the dividends and interest payments are typically not passed through to the pension funds. Most pension funds invest exclusively through external asset managers, and the standard contractual terms include reinvestment of dividends and interest payments rather than distributing these payments back to the pension fund. Thus, most pension funds need to submit redemption requests to external managers to cover their cash flow shortfalls.

Nevertheless, investment income can be an important source of cash flow that does not require transactions. In Online Appendix Figure A.2, we add the annual income from investment activities to the net cash flow obtained through PPD. We consider either a narrower measure of investment income that includes only dividends and interest payments, or a broader measure that also adds cash flows from security lending and other investment activities.[13] Panel A shows that the income from dividends and interest payments has declined from 2.8% in 2001 to 1.8% of pension assets in 2023.[14] Panel B shows that even if these payments were passed through to the pension funds, they would not be sufficient to meet the cash needs at the end of our sample period. For instance, the combined cash flows from operations and investment activity turn negative after 2008 and fluctuate around -1.0% of pension assets. For most pension funds, the investment income is insufficient to cover the average predictable outflows as *%CF Fit* is -2.5%. Any residual negative cash flow shocks add further liquidity demands on top of this baseline.

To validate the robustness of the investment income reported in PPD, we also compute investment income directly from the holdings data. For each pension fund, we aggregate the interest (coupon) and dividend payments received on individual securities, weighting by position size. Figure A.3 shows that investment income amounts to roughly 2.5% of pension fund assets on average. Moreover, Panel B indicates that the investment income reported in PPD and the measure constructed from the FOIA holdings sample are of similar magnitude and are correlated.[15]

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

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

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

[15]On average, the FOIA-based measure exceeds PPD by 0.50%. This likely reflects the fact that dividends and coupons are frequently reinvested automatically and thus may not even be recorded as investment income in PPD.

and coupons relative to total fixed income.

Finally, we examine the robustness of our results on the effect of pension fund cash flows on asset class flows by controlling for the investment income. In Online Appendix Tables C.3 and C.4, we control for the broad and narrow measures of investment income as a percentage of pension assets. While we do observe that the investment income is positively related to the flows in fixed income and equities, the coefficients on residual cash outflows remain unaffected. After controlling for investment income, negative residual cash outflows result in sizable sales of equities and alternatives.

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

5.2 Negative Cash Flows and Rebalancing

The liquidity-driven flows induced by negative cash flows differ significantly from rebalancing flows driven by market movements. To separate these effects, we include two proxies for rebalancing in the specifications. The first proxy, the lagged allocation gap, is more specific to the pension fund setting, and captures pension funds' gradual adjustments toward evolving target allocations over time (Andonov and Rauh, 2022; Begenau, Liang, and Siriwardane, 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 and Lee, 2025). Both proxies for rebalancing significantly affect pension fund flows, but cash flows remain a distinct determinant of flows.

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

In our main analysis, we use 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.5 shows that the results are robust to replacing the time fixed effects with the difference in returns between equities and fixed income. The benchmark returns ($R^{BM}_{j,t}$) are the median returns of all pension funds that operate with the same fiscal year end. We find that a 10 percentage point equity–bond return difference is associated with a 0.9% inflow to cash & fixed income and 0.7% outflow from equities. Importantly, the coefficients on predictable and residual cash flows remain the same.

Table 8 aims to further disentangle cash-flow-driven from rebalancing flows. Using the asset class benchmark returns, we split the sample into periods when equity returns are higher than fixed income returns, and vice versa. The rebalancing hypothesis posits that pension funds trade in a contrarian way by selling recent winners to realign toward target allocations. This hypothesis predicts that pension funds sell outperforming assets, so when fixed income outperforms equity, we should not observe outflows from equity.

However, we find that the liquidity-induced sales due to negative cash flows do not change conditional on 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.

Finally, Figure 4 visually shows that both the aggregate pension fund industry as a whole (Panel A) as well as the average pension fund (Panel B) sell equities during periods of negative stock market returns. Using the FOIA data, we construct quarterly equity flows using Equation (2) at the security level, which allows us to study selling behavior at a higher frequency than the annual data.[16] Equity selling during periods of negative stock returns becomes particularly pronounced after the GFC: in every quarter following the GFC with negative stock market returns, pension funds sell equities.

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

5.3 Heterogeneity Across Pension Funds

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.

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

[16] We start as of 2006Q4, due to the limited number of pension funds in our sample prior (see Figure 2). However, for those pension funds that report prior to 2006Q4, we find buying of equities during periods of negative stock market returns, consistent with the findings in Gabaix and Koijen (2022) using Flow of Funds data for the same period.

Table 9 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.

In addition, 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 liquid-asset-first approach and absorb negative cash flow shocks by selling the most liquid securities first.

To test this hypothesis, we focus on equities, as they absorb the majority of pension flows, and move to regressions at the security level.[17] We follow the same approach as in the previous section, but now calculate Equation (2) by replacing $A_{i,j,t}$ with the dollar amount invested in each security i by pension j at time t and $R^{BM}_{j,t}$ by the security-level return $R_{j,t}$ for each security j.

We merge pension funds' holdings with public databases to obtain detailed security-level returns.[18]

[17]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 6 for our FOIA sample renders $\%CF\ Fit$ insignificant across asset classes.

[18]The majority of pension funds report ISIN and CUSIP identifiers directly. When these are not reported, we match equity securities by name to obtain the corresponding ISIN or CUSIP.

For U.S. stocks, we use the CRSP U.S. Stock Database; for global stocks, the Compustat Global Security Daily Database; and for U.S. Treasuries, the CRSP U.S. Treasury and Inflation Series.

When the securities are not available in CRSP or Compustat, we assume the stock earned the benchmark return: the Russell 3000 Index for U.S. equities and the MSCI ACWI ex U.S. Index for international equities. For bonds other than U.S. Treasuries, we use the Bloomberg U.S. 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 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. 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 10 show that following a positive cash flow shock, pension funds buy equities, consistent with our earlier findings in Table 6. In terms of economic magnitude, we find that a 1% cash flow shock results in additional buying of 0.00009% of each individual liquid stock, or 30% (= 0.00009/0.0003) relative to the average annual flow to each stock. Moreover, pension funds are less likely to buy the most illiquid stocks as measured by the negative interaction term β. Summing up δ and β, we find that pension funds only modestly buy or sell illiquid stocks when facing cash flow shocks. Columns (3) and (4) furthermore show that this effect is primarily driven by positive cash flow shocks, while pension funds are not less likely to sell illiquid stocks when facing negative cash flow shocks. We draw the same conclusion when using MVE as a measure for liquidity instead in Panel B.

We also study whether pension funds sell more U.S. Treasuries within their portfolio of fixed income assets, as arguably, U.S. Treasuries are the most liquid part of their portfolio. We therefore rerun model (4) for fixed income securities, whereby we interact the cash flows shocks with an indicator variable if the bond is a U.S. Treasury bond. Table 11 summarizes the results. Focusing on 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 5 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 do not distinguish between more and less liquid stocks and absorb negative cash flow shocks through pro-rata selling.

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

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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.

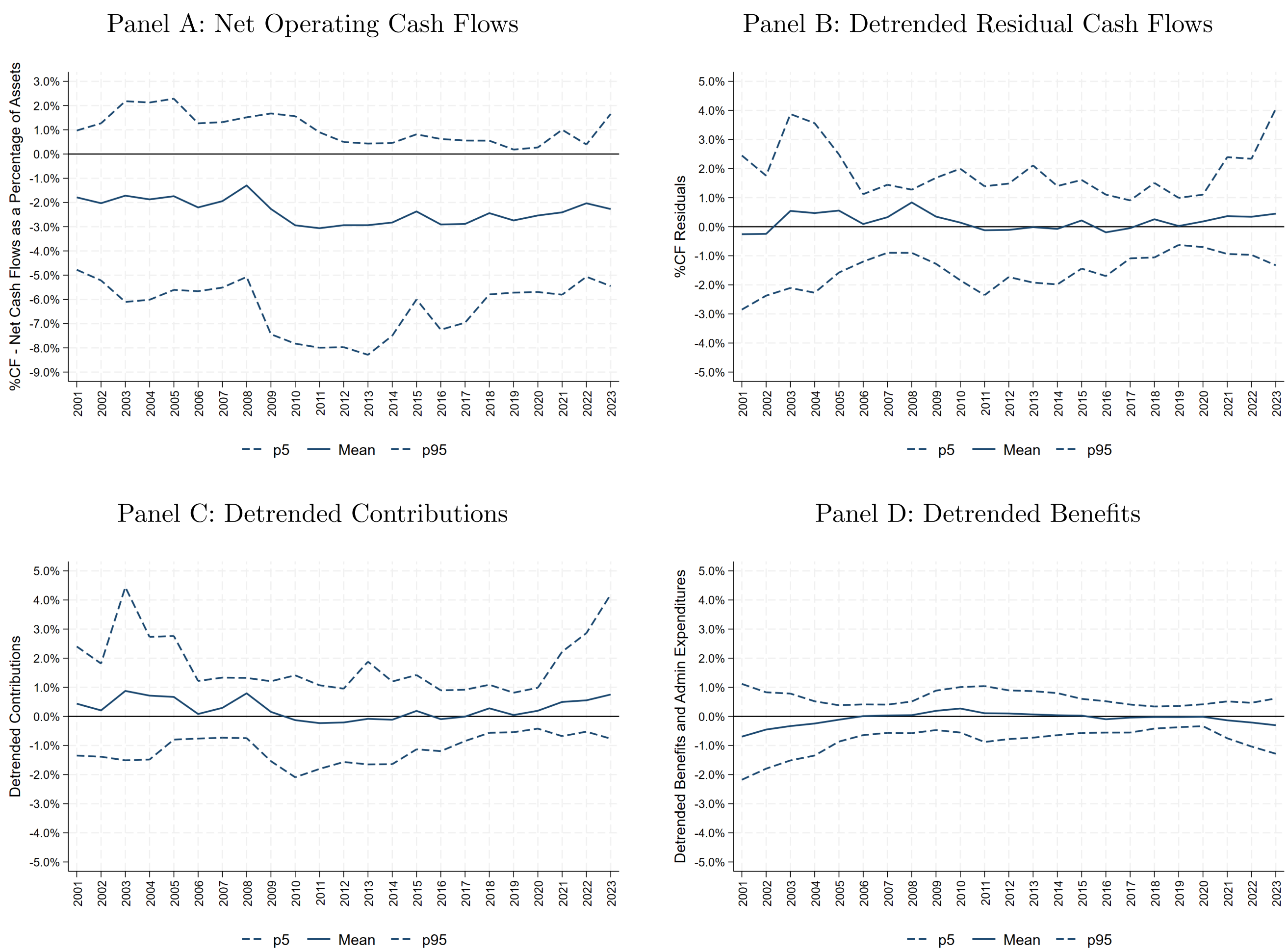


Figure 2: Pension Fund Holdings Data Coverage

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.

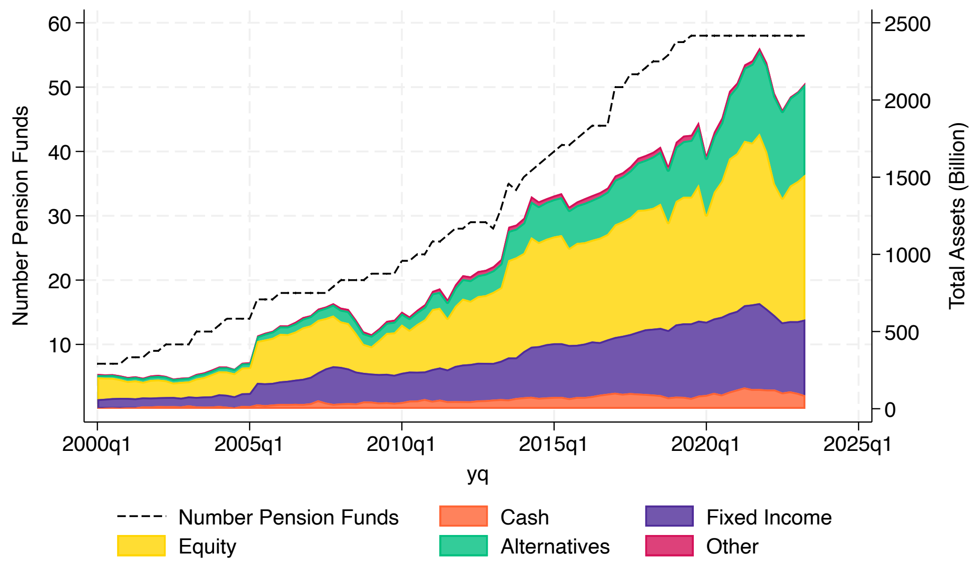


Figure 3: Pension Fund Holdings Data Detailed Asset Allocation

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.

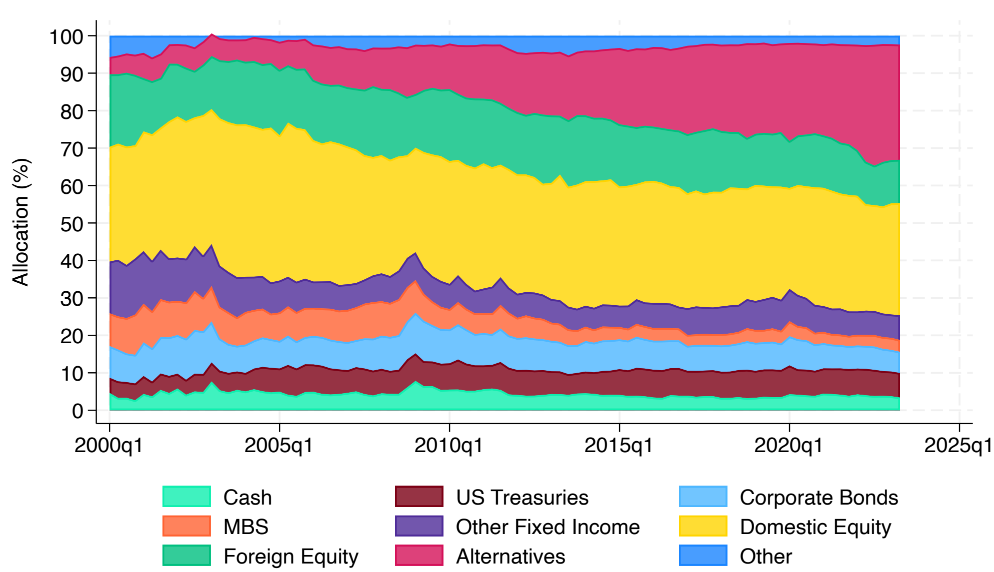
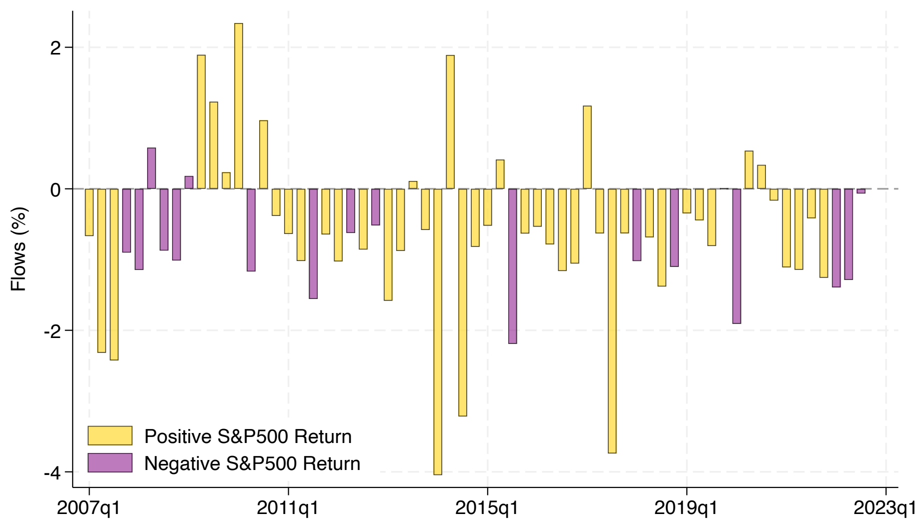


Figure 4: Equity Flows and S&P500 Returns

This figure shows the flows into equities for periods of positive and negative S&P500 returns. Flows into equities for pension fund i are computed as $Flow_{i,t} = \sum_{j=1}^{J} \frac{A_{i,j,t} - A_{i,j,t-1} \times (1+R_{j,t})}{TA_{i,t-1}}$, where $A_{i,j,t}$ is the dollar amount of assets invested by pension fund i in stock j in quarter t, $R_{j,t}$ is the return of stock j in that quarter, and $TA_{i,t-1}$ is the total amount of pension fund assets under management at the end of the previous quarter. We report the results for the sum of pension funds (Panel A) and for the average pension fund (Panel B) in our sample.

Panel A: Total Pension Fund



Panel B: Average Pension Fund

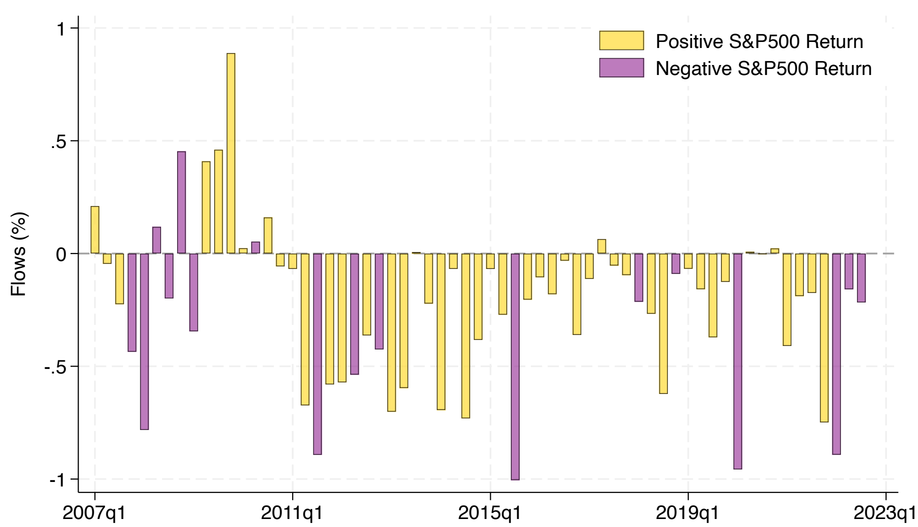


Table 1: Pension Fund Summary Statistics

This table presents summary statistics on pension fund cash flows, characteristics, and target asset allocations. We present statistics for the full sample of pension funds, and for the 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	Median	SD	Mean	Median	SD	Mean	Median	SD
Cash	161	49	385	28	11	53	4.2	2.9	4.3
Fixed Income									
Corporate Bonds	1184	660	1280	1024	649	1078	7.6	6.9	4.8
US Treasuries	160	67	201	116	58	143	6.7	4.8	7.2
MBS	749	274	1151	695	265	1073	4.5	4.1	3.6
Agencies + Foreign Gov Bonds	61	21	111	46	19	76	1.4	0.6	2.0
Other Fixed Income	150	60	229	128	55	176	7.3	5.9	6.7
Equity									
Equity Domestic	2432	1362	3137	1543	1063	1524	31.6	31.8	12.9
Equity Foreign	1643	699	2556	1040	580	1316	15.1	16.3	9.6
Alternatives									
Private Equity	78	25	114	74	21	108	9.9	7.5	10.0
Real Estate	157	64	266	93	50	120	5.5	5.7	3.8
Other	34	7	75	26	4	58	4.8	0.4	7.2

Table 3: Summary Statistics Derivatives Data

In this table, we summarize the derivatives data by category: linear derivatives (futures/forwards/swaps) and non-linear derivatives (options). We also split linear derivative contracts into equity, fixed income, currency, and other linear derivatives. The first column reports the fraction of pension fund-quarter observations that uses derivatives in each category. The remaining columns report the number of contracts, the total gross notional amount held (in billion USD), and the total gross notional amount as a fraction of total assets. We report the mean, median, and standard deviation.

	Usage (%)	**Contracts (#)**			**Gross Notional ($)**			**Gross Notional (%)**		
		Mean	Median	SD	Mean	Median	SD	Mean	Median	SD
Linear derivatives	71.2	106	31	178	1.0	0.0	3.7	2.6	0.0	5.0
Equity	53.3	11	4	22	0.0	0.0	0.6	0.1	0.0	0.5
Fixed Income	64.3	76	14	143	0.9	0.0	3.6	2.4	0.0	4.9
Currency	38.0	10	0	65	0.0	0.0	0.1	0.1	0.0	0.7
Other	25.5	9	0	32	0.0	0.0	0.3	0.1	0.0	0.3
Non-linear derivatives	72.9	26	7	42	0.3	0.0	2.3	0.5	0.0	3.8

Table 4: Target Asset Allocation and Cash Flows

In this table, observations are at the pension-fund-year level. The dependent variables measure the target asset allocation weights ($\omega_{i,t}$) of pension fund i in year t to cash & fixed income, equity, or alternatives. *%CF* is the ratio of net cash flows to pension fund assets at the beginning of the year. *%CF Fit* is the difference between fitted contributions and benefits scaled by pension assets. *%CF Predicted* is the difference between the predicted contributions and benefits scaled by pension assets. *%CF Volatility* is the volatility of *%CF* over the previous 10 years. We control for the lagged log of pension fund size and the lagged GASB funding ratio. The specifications include pension fund and 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 5: Asset Allocation to Cash and U.S. Treasuries and Cash Flows

In this table, observations are at the pension fund-year level. The dependent variable equals the actual allocation to cash and U.S. Treasury securities based on the holdings data obtained through 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.	0.109	0.109	0.109	0.109	0.108	0.108	0.108	0.108
%CF	-0.273	0.034						
	[0.279]	[0.163]						
%CF Fit			-0.838	-1.396				
			[0.485]	[1.234]				
%CF Predicted					-0.586	-0.455		
					[0.392]	[0.360]		
%CF Volatility							-0.009	-0.169
							[0.268]	[0.227]
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	735	735	735	735	592	592	592	592
R-squared	0.146	0.701	0.181	0.707	0.159	0.788	0.131	0.785

Table 6: Asset Class Investment Flows and Cash Flows

In this table, observations are at the pension-fund-year level. The dependent variables measure the investment flow of pension fund i in year t into cash & fixed income, equity, or alternatives. *%CF Fit* is the difference between fitted contributions and benefits scaled by pension assets at the beginning of the year. *%CF Residual* is the difference between residual contributions and residual benefits scaled by pension assets. Using piecewise decomposition, we split *%CF Residual* into %CF Residual $\text{Pos}_{i,t} = max(\%\text{CF Residual}_{i,t}, 0)$ and %CF Residual $\text{Neg}_{i,t} = min(\%\text{CF Residual}_{i,t}, 0)$. The reported p-value tests the null that the coefficients on the positive and negative components are equal. We control for the lagged log of pension fund size, lagged GASB funding ratio, and lagged allocation gap. The allocation gap captures the difference between the actual and target asset allocation ($\omega^{Target}_{i,j,t-1} - \omega^{Actual}_{i,j,t-1}$) 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.	-0.005	-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 7: Investment Income from Assets and Cash Flows

In this table, observations are at the pension fund-year level. The dependent variable equals the total investment income (dividends and coupons), relative to total equity and fixed income assets, based on the holdings data obtained through FOIA requests. *%CF* is the ratio of net cash flows to pension fund assets at the beginning of the year. *%CF Fit* is the difference between fitted contributions and benefits scaled by pension assets. *%CF Predicted* is the difference between the predicted contributions and benefits scaled by pension assets. *%CF Volatility* is the volatility of *%CF* over the previous 10 years. We control for the lagged log of pension fund size and the lagged GASB funding ratio. The specifications include 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.	0.037	0.037	0.037	0.037	0.037	0.037	0.037	0.037
%CF	0.067	0.026						
	[0.049]	[0.023]						
%CF Fit			0.071	-0.058				
			[0.070]	[0.081]				
%CF Predicted					0.064	0.007		
					[0.061]	[0.025]		
%CF Volatility							0.065	0.079
							[0.075]	[0.060]
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	741	741	741	741	622	622	622	622
R-squared	0.117	0.710	0.114	0.709	0.113	0.736	0.107	0.739

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

In this table, observations are at the pension-fund-year level. Panel A studies the subsample of observations in periods when equity returns are higher than fixed income returns. Panel B reports results for periods when equity returns are lower than fixed income returns. The dependent variables measure the investment flow of pension fund i in year t into cash & fixed income, equity, or alternatives. *%CF Fit* is the difference between fitted contributions and benefits scaled by pension assets at the beginning of the year. *%CF Residual* is the difference between residual contributions and residual benefits scaled by pension assets. Using piecewise decomposition, we split *%CF Residual* into $\%\text{CF Residual Pos}_{i,t} = max(\%\text{CF Residual}_{i,t}, 0)$ and $\%\text{CF Residual Neg}_{i,t} = min(\%\text{CF Residual}_{i,t}, 0)$. We control for the lagged log of pension fund size, lagged GASB funding ratio, and lagged allocation gap. The allocation gap captures the difference between the actual and target asset allocation ($\omega^{Target}_{i,j,t-1} - \omega^{Actual}_{i,j,t-1}$) of pension fund i in asset class j in year $t-1$. The specifications include pension fund and 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 $R^{BM}_{EQ,t} > R^{BM}_{FI,t}$						
Mean Dep. Var.	0.003	0.003	-0.034	-0.034	0.004	0.004
%CF Fit	0.362***	0.417***	0.505***	0.494***	0.203	0.170
	[0.105]	[0.113]	[0.134]	[0.134]	[0.125]	[0.116]
%CF Residuals	0.398***		0.521***		0.116**	
	[0.063]		[0.049]		[0.053]	
%CF Residuals Pos		0.497***		0.500***		0.057
		[0.067]		[0.069]		[0.035]
%CF Residuals Neg		-0.063		0.617***		0.389*
		[0.117]		[0.153]		[0.226]
Allocation Gap	0.371***	0.376***	0.390***	0.390***	0.264***	0.267***
	[0.062]	[0.062]	[0.052]	[0.052]	[0.028]	[0.029]
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Pension Fund FE	Yes	Yes	Yes	Yes	Yes	Yes
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 $R^{BM}_{EQ,t} < R^{BM}_{FI,t}$						
Mean Dep. Var.	-0.019	-0.019	-0.013	-0.013	0.001	0.001
%CF Fit	0.490***	0.502***	0.422***	0.413***	-0.029	-0.034
	[0.143]	[0.142]	[0.129]	[0.130]	[0.138]	[0.136]
%CF Residuals	0.902***		0.072		0.030	
	[0.064]		[0.054]		[0.024]	
%CF Residuals Pos		0.944***		0.042		0.013
		[0.034]		[0.034]		[0.018]
%CF Residuals Neg		0.103		0.629***		0.364**
		[0.188]		[0.134]		[0.184]
Allocation Gap	0.353***	0.355***	0.287***	0.291***	0.263***	0.261***
	[0.041]	[0.040]	[0.048]	[0.048]	[0.040]	[0.039]
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Pension Fund FE	Yes	Yes	Yes	Yes	Yes	Yes
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 9: 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 10: Equity 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 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.	0.032	0.035	0.032	0.035
%CF Residuals	0.009***	0.012***		
	[0.002]	[0.002]		
%CF Residuals Pos			0.012***	0.014***
			[0.002]	[0.003]
%CF Residuals Neg			-0.011	-0.005
			[0.006]	[0.008]
%CF Residuals × Amihud High	-0.006**	-0.006*		
	[0.002]	[0.003]		
%CF Residuals Pos × Amihud High			-0.008***	-0.008***
			[0.002]	[0.002]
%CF Residuals Neg × Amihud High			0.007	0.017
			[0.010]	[0.014]
Amihud High	0.024***		0.028**	
	[0.007]		[0.009]	
Controls	Yes	Yes	Yes	Yes
Pension Fund FE	Yes	Yes	Yes	Yes
Year FE	Yes		Yes	
Security-Year FE		Yes		Yes
Observations	1.51e+06	1.33e+06	1.51e+06	1.33e+06
R-squared	0.004	0.242	0.004	0.242

Panel B: Market Value Equity (MVE)	(1)	(2)	(3)	(4)
Mean Dep. Var.	0.033	0.035	0.033	0.035
%CF Residuals	0.009***	0.013***		
	[0.002]	[0.002]		
%CF Residuals Pos			0.012***	0.015***
			[0.002]	[0.003]
%CF Residuals Neg			-0.008	-0.001
			[0.007]	[0.009]
%CF Residuals × MVE Low	-0.009***	-0.011***		
	[0.002]	[0.002]		
%CF Residuals Pos × MVE Low			-0.010***	-0.012***
			[0.002]	[0.002]
%CF Residuals Neg × MVE Low			-0.002	0.001
			[0.006]	[0.007]
MVE Low	0.016***		0.018***	
	[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	1.52e+06	1.34e+06	1.52e+06	1.34e+06
R-squared	0.004	0.242	0.004	0.242

Table 11: 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. *$p < .10$; **$p < .05$; ***$p < .01$.

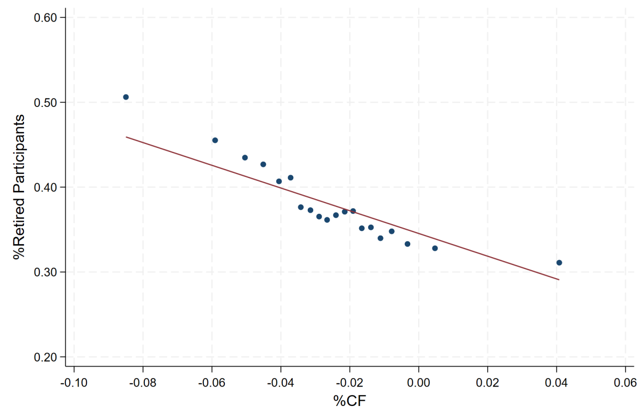
	(1)	(2)	(3)	(4)
Mean Dep. Var.	-0.084	-0.083	-0.084	-0.083
%CF Residuals	0.0037***	0.0035***		
	[0.0007]	[0.0010]		
%CF Residuals Pos			0.0077***	0.0063***
			[0.0009]	[0.0011]
%CF Residuals Neg			-0.0089***	-0.0059**
			[0.0018]	[0.0020]
%CF Residuals × U.S. Treasuries	0.0105	0.0172		
	[0.0102]	[0.0128]		
%CF Residuals Pos × U.S. Treasuries			-0.0017	0.0168
			[0.0117]	[0.0136]
%CF Residuals Neg × U.S. Treasuries			0.0534**	0.0187
			[0.0202]	[0.0273]
U.S. Treasuries	-0.3312***		-0.3166***	
	[0.0120]		[0.0135]	
Controls	Yes	Yes	Yes	Yes
Pension Fund FE	Yes	Yes	Yes	Yes
Year FE	Yes		Yes	
Security-Year FE		Yes		Yes
Observations	5.03e+06	3.19e+06	5.03e+06	3.19e+06
R-squared	0.028	0.296	0.028	0.296

Online Appendix A: Cash Flow Measures

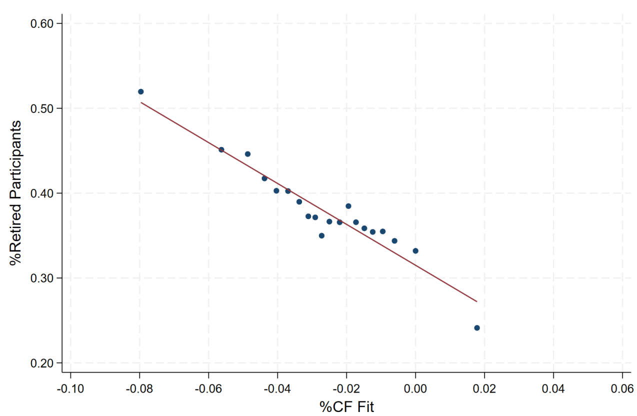
Figure A.1: Pension Fund Cash Flows and the Percentage of Retired Participants

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.

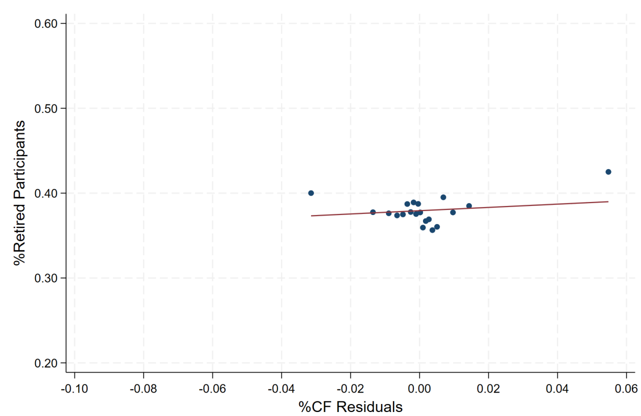
Panel A: Net Operating Cash Flows



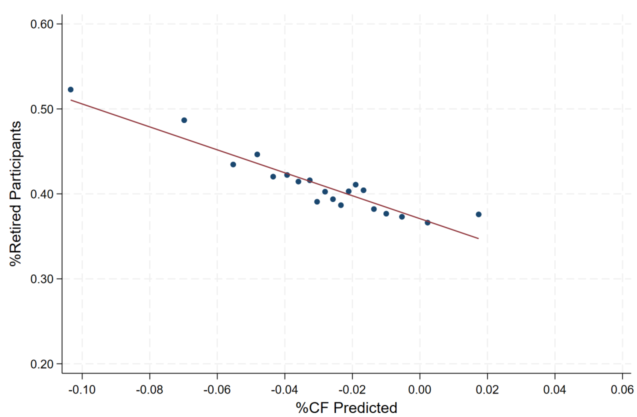
Panel B: Fitted Cash Flows



Panel C: Residual Cash Flows



Panel D: Predicted Cash Flows



Panel E: Cash Flow Shocks

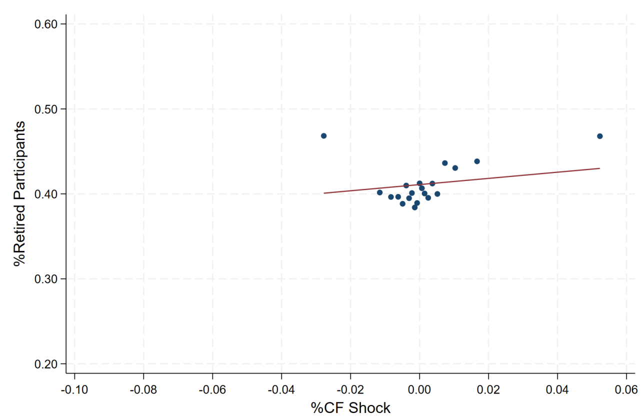


Table A.1: Correlations of Cash Flow Measures

	%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

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

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

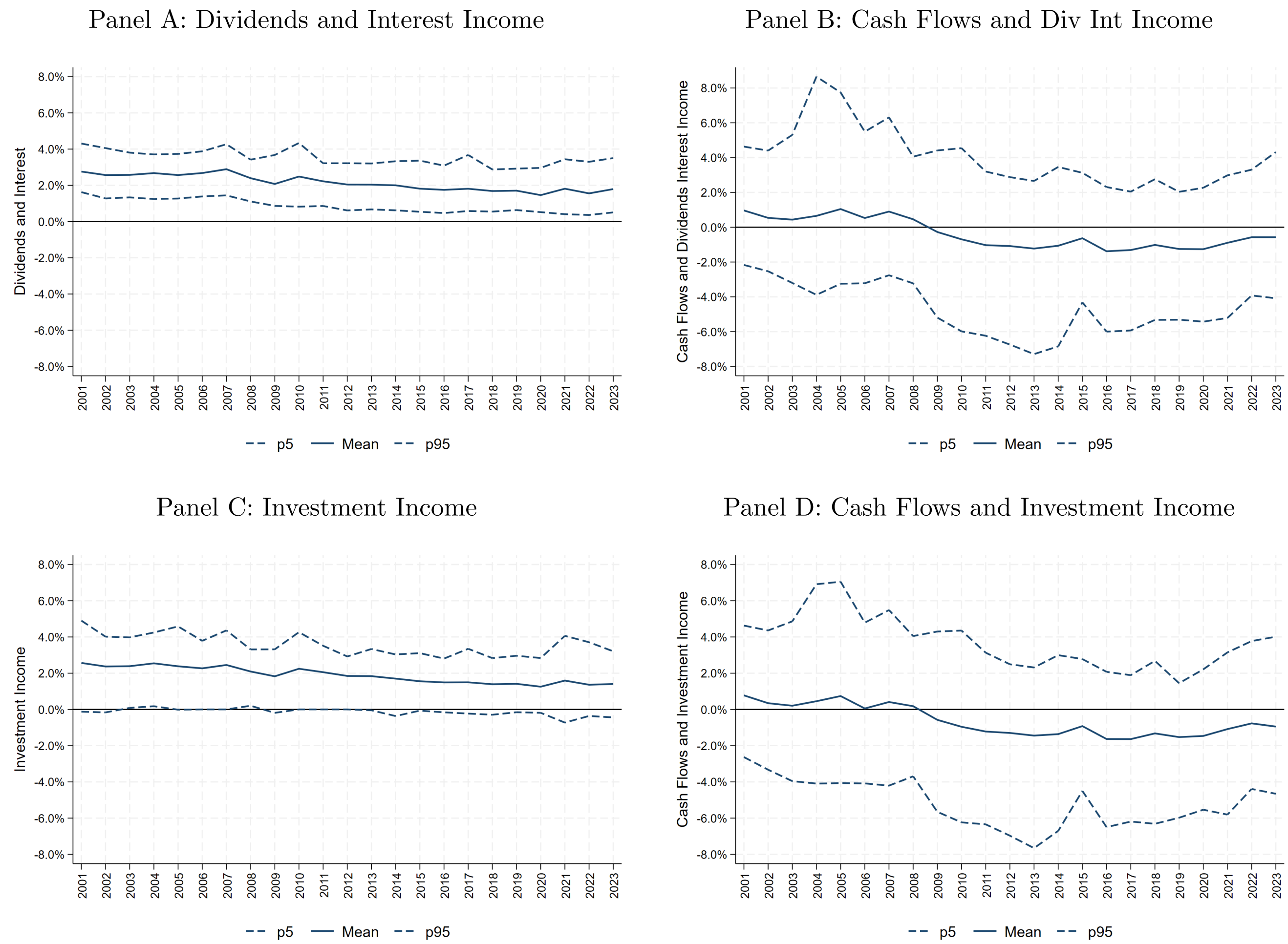
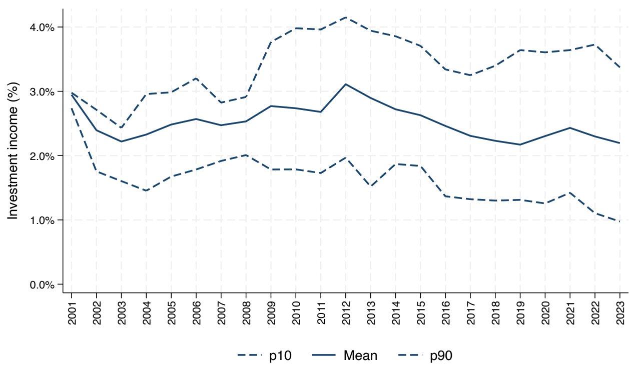


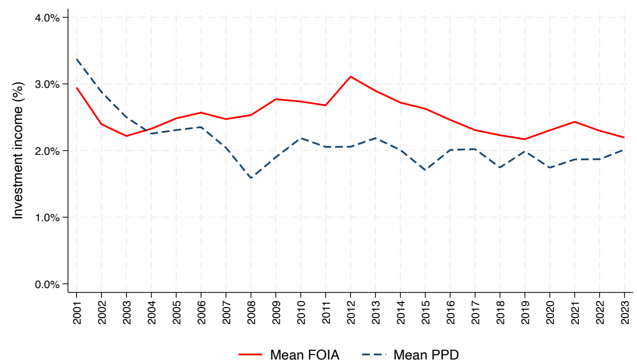
Figure A.3: Investment Income from Holdings Data

We construct a direct measure of investment income by aggregating, at the pension-fund level, all interest (coupon) and dividend payments on individual securities in our FOIA holdings data (weighted by total position size). Panel A shows this direct investment income measure as a percentage of assets over time. Panel B compares our direct measure with the investment income reported in PPD (interest and dividends only).

Panel A: Dividends and Interest Income FOIA



Panel B: Dividends and Interest Income FOIA vs PPD



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 59 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

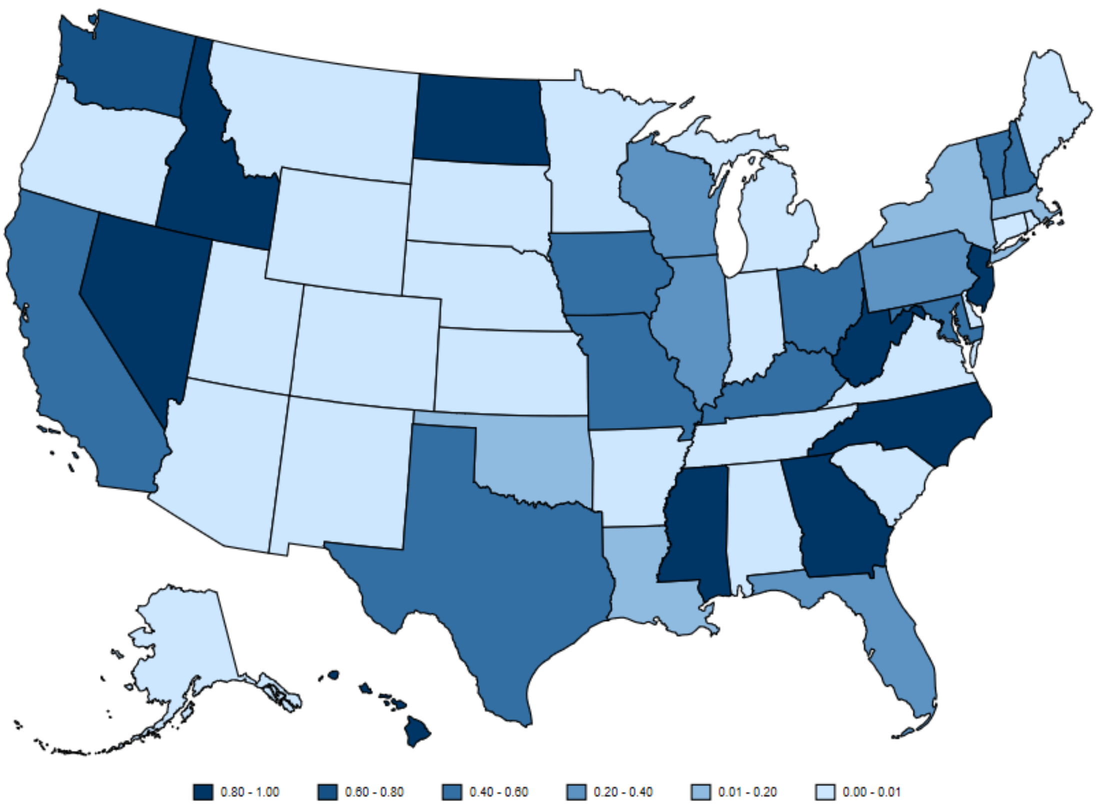


Table B.1: Probability of Pension Funds Disclosing Holdings Data

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. = 21.3%)					
	(1)	(2)	(3)	(4)	(5)	(6)
%CF	0.430	-0.607				
	[0.411]	[0.948]				
%CF Fit			0.836	-2.130	0.818	-2.146
			[1.241]	[1.825]	[1.242]	[1.821]
%CF Residuals			0.279	0.040		
			[0.256]	[0.258]		
%CF Residuals Pos					0.195	0.007
					[0.297]	[0.260]
%CF Residuals Neg					1.055	0.349
					[2.123]	[1.706]
Pension Fund Size	0.061***	0.092***	0.061***	0.095***	0.061***	0.095***
	[0.018]	[0.032]	[0.018]	[0.032]	[0.018]	[0.032]
GASB Funding Status	0.103	-0.058	0.090	-0.026	0.084	-0.028
	[0.139]	[0.224]	[0.141]	[0.229]	[0.140]	[0.228]
Return	-0.002	0.403	0.005	0.381	0.009	0.383
	[0.351]	[0.402]	[0.350]	[0.393]	[0.352]	[0.397]
%Equity	0.044	0.061	0.056	0.018	0.055	0.016
	[0.347]	[0.423]	[0.352]	[0.413]	[0.351]	[0.414]
%Real Assets	-0.189	-0.318	-0.189	-0.291	-0.194	-0.291
	[0.432]	[0.488]	[0.431]	[0.486]	[0.429]	[0.485]
%Hedge Funds	0.298	0.566	0.304	0.525	0.306	0.525
	[0.382]	[0.531]	[0.383]	[0.527]	[0.384]	[0.528]
%Private Equity	-0.423	-0.550	-0.424	-0.571	-0.423	-0.570
	[0.414]	[0.535]	[0.415]	[0.535]	[0.415]	[0.535]
%Other Alternatives	0.037	0.518	0.032	0.544	0.029	0.545
	[0.473]	[0.588]	[0.470]	[0.594]	[0.468]	[0.595]
Year-Reporting-Month FE	Yes	Yes	Yes	Yes	Yes	Yes
State FE		Yes		Yes		Yes
Observations	3,251	2,397	3,251	2,397	3,251	2,397

Online Appendix C: Pension Fund Aggregate Flows

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

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

In this table, observations are at the pension-fund-year level. The dependent variables measure the investment flow of pension fund i in year t into cash & fixed income, equity, or alternatives. *%CF Predicted* is the difference between the predicted contributions and benefits scaled by pension assets at the beginning of the year. *%CF Shock* is estimated using the differences between the realized contributions (benefits) and the predicted contributions (benefits), scaled by pension assets. Using piecewise decomposition, we split *%CF Shock* into %CF Shock $\text{Pos}_{i,t} = max(\text{\%CF Shock}_{i,t}, 0)$ and %CF Shock $\text{Neg}_{i,t} = min(\text{\%CF Shock}_{i,t}, 0)$. The reported p-value tests the null that the coefficients on the positive and negative components are equal. We control for the lagged log of pension fund size, lagged GASB funding ratio, and lagged allocation gap. The allocation gap captures the difference between the actual and target asset allocation ($\omega^{Target}_{i,j,t-1} - \omega^{Actual}_{i,j,t-1}$) of pension fund i in asset class j in year $t-1$. The specifications include pension fund and 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 6: 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 ($\omega^{Target}_{i,j,t-1} - \omega^{Actual}_{i,j,t-1}$) 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	-0.026	-0.026	-0.001	-0.001
%CF Fit	0.268	0.305	-0.043	-0.035	0.168	0.110
	[0.219]	[0.212]	[0.324]	[0.327]	[0.313]	[0.315]
%CF Residuals	0.154		0.531***		0.265**	
	[0.101]		[0.082]		[0.103]	
%CF Residuals Pos		0.297***		0.576***		0.086
		[0.088]		[0.102]		[0.104]
%CF Residuals Neg		-0.253***		0.403***		0.777***
		[0.094]		[0.108]		[0.089]
Allocation Gap	0.236**	0.241**	0.345***	0.348***	0.247***	0.260***
	[0.098]	[0.101]	[0.053]	[0.054]	[0.043]	[0.041]
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	692	692	692	692	688	688
R-squared	0.297	0.307	0.373	0.374	0.357	0.369
p-value test		0.00		0.30		0.00

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

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

In this table, observations are at the pension-fund-year level. The dependent variables measure the investment flow of pension fund i in year t into cash & fixed income, equity, or alternatives. *%CF Fit* is the difference between fitted contributions and benefits scaled by pension assets at the beginning of the year. *%CF Residual* is the difference between residual contributions and residual benefits scaled by pension assets. Using piecewise decomposition, we split *%CF Residual* into %CF Residual $\text{Pos}_{i,t} = max(\text{\%CF Residual}_{i,t}, 0)$ and %CF Residual $\text{Neg}_{i,t} = min(\text{\%CF Residual}_{i,t}, 0)$. The reported p-value tests the null that the coefficients on the positive and negative components are equal. We control for the lagged log of pension fund size, lagged GASB funding ratio, and lagged allocation gap. The allocation gap captures the difference between the actual and target asset allocation ($\omega^{Target}_{i,j,t-1} - \omega^{Actual}_{i,j,t-1}$) 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.	-0.006	-0.006	-0.026	-0.026	0.003	0.003
%CF Fit	0.429***	0.451***	0.453***	0.449***	0.064	0.049
	[0.105]	[0.107]	[0.122]	[0.121]	[0.113]	[0.114]
%CF Residuals	0.447***		0.481***		0.086*	
	[0.065]		[0.047]		[0.045]	
%CF Residuals Pos		0.565***		0.453***		0.009
		[0.071]		[0.065]		[0.043]
%CF Residuals Neg		0.009		0.584***		0.376**
		[0.108]		[0.100]		[0.144]
Allocation Gap	0.344***	0.348***	0.332***	0.333***	0.250***	0.252***
	[0.050]	[0.050]	[0.048]	[0.048]	[0.025]	[0.026]
Dividends Interest Income	0.103	0.121	0.185*	0.181*	-0.010	-0.023
	[0.084]	[0.088]	[0.098]	[0.097]	[0.091]	[0.094]
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Pension Fund FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,430	2,430	2,430	2,430	2,420	2,420
R-squared	0.369	0.375	0.356	0.356	0.244	0.248
p-value test		0.00		0.35		0.03

Table C.4: Asset Class Investment Flows and Cash Flows - Investment Income

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

In this table, observations are at the pension-fund-year level. The dependent variables measure the investment flow of pension fund i in year t into cash & fixed income, equity, or alternatives. *%CF Fit* is the difference between fitted contributions and benefits scaled by pension assets at the beginning of the year. *%CF Residual* is the difference between residual contributions and residual benefits scaled by pension assets. Using piecewise decomposition, we split *%CF Residual* into %CF Residual $\text{Pos}_{i,t} = max(\%\text{CF Residual}_{i,t}, 0)$ and %CF Residual $\text{Neg}_{i,t} = min(\%\text{CF Residual}_{i,t}, 0)$. The reported p-value tests the null that the coefficients on the positive and negative components are equal. We control for the lagged log of pension fund size, lagged GASB funding ratio, and lagged allocation gap. The allocation gap captures the difference between the actual and target asset allocation ($\omega^{Target}_{i,j,t-1} - \omega^{Actual}_{i,j,t-1}$) 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.	-0.006	-0.006	-0.026	-0.026	0.003	0.003
%CF Fit	0.418***	0.444***	0.439***	0.435***	0.131	0.111
	[0.099]	[0.102]	[0.122]	[0.121]	[0.121]	[0.118]
%CF Residuals	0.443***		0.482***		0.101*	
	[0.064]		[0.046]		[0.057]	
%CF Residuals Pos		0.560***		0.464***		0.009
		[0.069]		[0.064]		[0.043]
%CF Residuals Neg		0.017		0.549***		0.435**
		[0.107]		[0.105]		[0.179]
Allocation Gap	0.341***	0.344***	0.345***	0.345***	0.262***	0.264***
	[0.048]	[0.048]	[0.047]	[0.047]	[0.026]	[0.026]
Investment Income	0.135**	0.140**	0.210**	0.210**	0.014	0.011
	[0.063]	[0.062]	[0.095]	[0.095]	[0.076]	[0.076]
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Pension Fund FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,614	2,614	2,614	2,614	2,601	2,601
R-squared	0.371	0.377	0.361	0.361	0.241	0.245
p-value test		0.00		0.56		0.03

Table C.5: Asset Class Investment Flows and Cash Flows - Rebalancing Flows

Robustness test of Table 6: We control for the difference in returns between equities and fixed income ($R^{BM}_{EQ,t} - R^{BM}_{FI,t}$) instead of including 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.6: 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.	0.0404	0.0404	0.0404	0.0404	0.0382	0.0382	0.0382	0.0382
%CF	-0.014	0.105						
	[0.160]	[0.129]						
%CF Fit			-0.244	-0.611				
			[0.251]	[0.459]				
%CF Predicted					-0.097	-0.197		
					[0.188]	[0.190]		
%CF Volatility							0.380	-0.025
							[0.209]	[0.088]
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	771	771	771	771	628	628	628	628
R-squared	0.057	0.725	0.069	0.727	0.039	0.793	0.052	0.790
Panel B: Allocation to U.S. Treasuries								
Mean Dep. Var.	0.0686	0.0686	0.0686	0.0686	0.0695	0.0695	0.0695	0.0695
%CF	-0.258	-0.069						
	[0.240]	[0.119]						
%CF Fit			-0.598	-0.749				
			[0.493]	[1.112]				
%CF Predicted					-0.483	-0.230		
					[0.386]	[0.243]		
%CF Volatility							-0.380	-0.145
							[0.296]	[0.171]
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	735	735	735	735	592	592	592	592
R-squared	0.095	0.736	0.113	0.738	0.109	0.814	0.093	0.813

Table C.7: Income from Dividends and Coupons and Cash Flows

In this table, observations are at the pension fund-year level. The dependent variable equals the investment income from dividends payments relative to equity assets (Panel A) or from coupons relative to fixed income assets (Panel B), based on the holdings data obtained through FOIA requests. *%CF* is the ratio of net cash flows to pension fund assets at the beginning of the year. *%CF Fit* is the difference between fitted contributions and benefits scaled by pension assets. *%CF Predicted* is the difference between the predicted contributions and benefits scaled by pension assets. *%CF Volatility* is the volatility of *%CF* over the previous 10 years. We control for the lagged log of pension fund size and the lagged GASB funding ratio. The specifications include 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: Dividends (relative to equity assets)								
Mean Dep. Var.	0.021	0.021	0.021	0.021	0.021	0.021	0.021	0.021
%CF	0.005	0.016						
	[0.032]	[0.021]						
%CF Fit			-0.005	-0.033				
			[0.048]	[0.132]				
%CF Predicted					0.002	0.003		
					[0.039]	[0.032]		
%CF Volatility							0.029	-0.047
							[0.049]	[0.073]
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	741	741	741	741	622	622	622	622
R-squared	0.149	0.619	0.149	0.618	0.134	0.644	0.136	0.646
Panel B: Coupons (relative to fixed income assets)								
Mean Dep. Var.	0.059	0.059	0.059	0.059	0.060	0.060	0.060	0.060
%CF	0.084	0.053						
	[0.077]	[0.051]						
%CF Fit			0.040	-0.144				
			[0.107]	[0.223]				
%CF Predicted					0.072	0.072		
					[0.102]	[0.077]		
%CF Volatility							0.119	0.171
							[0.106]	[0.087]
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	741	741	741	741	622	622	622	622
R-squared	0.172	0.602	0.167	0.602	0.168	0.636	0.168	0.639