Same Dollar, Different Impact: Investor Flows are Not Equally Price-Moving*

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Abstract

Mutual fund flows generate substantial price impact, amplify fragility, and trigger fire sales. We document a stark contrast for separate accounts—the dominant investment vehicle for institutional investors: separate account flows generate essentially no price impact, fragility, or fire-sale risk. This pattern holds within mutual fund–separate account twins managed under identical strategies by same managers. Using trade-level data from a major transition manager, we show that these specialized intermediaries that execute institutional capital allocations significantly reduce trading costs and dampen price impact. Our findings reveal large heterogeneity in how investor demand transmits to prices—not all flows are equally price-moving.

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1 Introduction

One central theme in asset-pricing research is whether, and by how much, investor demand moves asset prices (e.g. Duffie, 2010). Using the most readily available flows and holdings data of mutual funds, a large literature shows that mutual fund flows generate sizable price impact (e.g., Lou, 2012; Li, 2022; Ben-David et al., 2022a), amplify price fragility (e.g., Greenwood and Thesmar, 2011; Huang et al., 2025b), and trigger fire-sale dynamics (e.g., Coval and Stafford, 2007). These findings have motivated a growing literature that estimates "price multipliers" and shaped prevailing views on the extent to which demand pressures transmit into prices (e.g., Koijen and Yogo, 2019; Gabaix and Koijen, 2021; Koijen et al., 2024).

Yet mutual funds represent only one segment of the delegated investment universe and predominantly serve retail investors.[1] A comparable share of delegated assets is managed through institutional vehicles (IVs), such as separate accounts[2] and commingled funds, whose flow dynamics and pricing implications remain far less understood. Whether the significant flow-induced price effects documented for mutual funds are pervasive across investment vehicles, or instead specific to retail-oriented mutual funds, remains an important unanswered question for the extensive literature that investigates investors' demand and asset prices.

In this paper, we address this question by studying the effects of IV flows on asset prices. Our analysis draws on a novel quarterly holdings dataset of separate accounts—the dominant investment vehicle for institutional investors such as pensions, insurance companies, endowments, and sovereign wealth funds. Although the total scale of the separate

[1] Based on the ICI Fact Book (2024), more than 90% of the assets of mutual funds are held by household and retail investors.

[2] Separate accounts are also referred to as separately managed accounts.

account sector rivals that of the mutual fund industry, it has received much less attention in the literature.

Our findings reveal a stark contrast with mutual funds. Separate account flows generate essentially no price impact, do not amplify price fragility, and do not trigger fire-sale dynamics, even though the magnitudes and variations of separate account flows are comparable to those of mutual funds. To sharpen the comparison, we examine separate account–mutual fund "twins," pairs that are managed under the same strategies by the same managers (Huang et al., 2025a). Even within these twins, separate account flows barely move prices, whereas flows of their mutual fund counterparts create substantial price impact, indicating that the differences are not driven by investment strategies employed by mutual funds and separate accounts. Moreover, the contrast persists after controlling for market-wide liquidity at the time flows occur, suggesting it is not primarily driven by institutional investors' ability to time favorable liquidity conditions when allocating capital among separate accounts.

We hypothesize that transition managers play an important role in mitigating the price impact of institutional flows. Institutional capital allocations are often executed by specialized transition managers, who are hired by institutional investors to implement capital transitions with the objective of minimizing market disruption.[3] To shed light on this mechanism, we obtain transaction-level data of 1,787 transition programs from a leading transition manager.[4] Relative to mutual funds, we find that these specialized intermediaries reduce trading costs by 80% to 90% and significantly suppress the price dislocations associated with institutional capital allocation. Overall, our findings indicate

[3]Some of the leading transition managers are Russell Investments, State Street Corporation, Citi, Bank of New York Mellon, and Northern Trust Corporation.

[4]A transition program moves a legacy portfolio to a target portfolio or moves capital from or into cash (also known as "one-sided events"). See Section 6 for more institutional details of transition management.

that not all flows are equally "price-moving" and highlight substantial heterogeneity in how different investment vehicles transmit demand shocks, even though these investment vehicles could be managed under the same investment strategies.

Our analysis is built on a novel dataset of quarterly holdings of U.S. equity separate accounts spanning from 2001 to 2024. To set the stage, we first examine how separate account holdings change in response to institutional capital flows. We find that, similar to mutual funds, capital flows of separate accounts create flow-induced demand: existing holdings of separate accounts increase by 0.78% with 1% inflow and decrease by 0.93% with 1% outflow. Thus, flows of separate accounts create demand on existing portfolio holdings similar to mutual fund flows. However, it is worth noting that unlike retail mutual fund investors, institutional investors often use transition managers to execute trades associated with large capital flows.[5]

We then assess the price impact of separate account flow-induced trading, using the measure of Lou (2012). We find that the flow-induced price impact of separate accounts is economically negligible and statistically insignificant across different specifications. In sharp contrast, when the aggregate mutual fund sector buys 1% of a stock's shares outstanding in response to flows, the stock experiences a 1.64% contemporaneous price run-up (t-statistic = 5.80), followed by a significant reversal.

We next examine flow-induced fire-sale dynamics following Coval and Stafford (2007), who document that mutual funds experiencing extreme outflows tend to fire sell existing holdings, creating significant downward price pressure on stocks held in common by distressed funds. We again find stark differences between separate accounts and mutual funds. For stocks mostly exposed to mutual fund fire sales, we observe a significant price

[5]Investments held in mutual funds are not eligible for transition manager services (Meketa Investment Group, 2019).

decline of -2.27% (t-statistic $= -5.82$) through the end of the fire-sale quarter. For separate account fire sales, even though the most affected stocks experience larger demand shocks, the corresponding price decline is much more modest: the cumulative abnormal return through the quarter-end is -0.57%, which is statistically indistinguishable from zero with a t-statistic of -1.24. This sharp contrast indicates that separate account flow-led fire sales exert far smaller price effects than those by mutual funds.

Having established the differential price impact of mutual funds and separate accounts, we next examine the implications for flow-induced price fragility following Greenwood and Thesmar (2011). The intuition is straightforward: if flow-induced trading generates non-fundamental price pressures, then variation in such trading should create non-fundamental return volatility for the affected stocks. We find that mutual fund flow-induced fragility imposes substantial non-fundamental risks on stocks, whereas the effect of separate account flow-induced fragility is economically small and statistically insignificant after controlling for the mutual fund effects.

A potential explanation for our findings is that the investment strategies employed by separate accounts differ substantially from those of mutual funds, yielding different capacities to accommodate flows. To test these hypotheses, we exploit mutual fund–separate account "twins," which are managed under the same strategy by the same portfolio managers.[6] We observe the same patterns among these twins, indicating that the differential price impacts of mutual fund and separate account flows are not driven by differences in investment strategies.

Another possible explanation is that institutional investors, like pension funds, endowments, and insurance companies, are better at "timing" favorable market-wide liquidity

[6] Huang et al. (2025a) show that the majority of mutual funds have twin IVs serving institutional investors.

conditions when allocating capital among separate accounts. That is, these institutions move capital in and out of separate accounts when market-wide liquidity is higher. To rule out this hypothesis, we use the aggregate market liquidity measure of Pástor and Stambaugh (2003) and divide the sample into two equal halves based on liquidity levels. Within each subsample, we re-estimate the flow-induced price impact. We find that the price impact of separate account flows remains insignificant and negligible in both low- and high-liquidity periods, whereas mutual fund flow-induced price impacts are significant in both.

To understand why separate account flows generate minimal price impact, we examine the role of transition managers—the specialized intermediaries tasked with executing institutional portfolio allocations with the goal of minimizing transaction costs and price impact. Transition managers possess expertise in accessing a broad array of trading venues, limiting information leakage, and exploiting scale and network externalities.[7] These capabilities enable them to reduce implementation shortfall and prevent the price dislocations that typically accompany sizable flows. In contrast, mutual funds are structurally obligated to prioritize daily liquidity over minimizing execution costs, as the rigid Net Asset Value (NAV) pricing rule mechanically forces portfolio managers to trade to accommodate daily investor subscriptions and redemptions.

To this end, we obtain trade-level data on 1,787 U.S. equity transition programs executed by a leading transition manager over 2013–2021. On average, these programs involve $248 million in U.S. equity trades and are typically completed within five days. By analyzing the transaction-level data, we confirm that trades executed by this transition manager generate negligible price impact. Moreover, we estimate that transaction

[7] For example, in a case study reported by Russell Investments (2020), they used 72 execution venues for 1,900 equity trades.

costs for transition programs are only about 10%–20% of those borne by mutual funds. We also find evidence that transition management service is more likely to be used by institutional investors for larger capital allocation. Taken together, these findings indicate that transition managers can effectively mitigate flow-induced price dislocations of institutional capital.

While transition managers play an important role, they may not be the sole driver of the sharp contrast in flow-induced price impact between mutual funds and separate accounts. Even when institutional investors do not use transition management services and leave trade execution of flows to asset managers, asset managers may prioritize institutional mandates and treat institutional flows more carefully. To the extent that such choices attenuate price pressure, part of the contrast that we document may reflect differences in trading behavior and execution quality of asset managers rather than transition management. In fact, these additional channels also reinforce our conclusion that investor demand can transmit to prices in highly heterogeneous ways: not all flows are equally "price-moving."

Our results have several implications for the large literature examining investor demand and asset prices. First, they highlight substantial heterogeneity in how different investment vehicles transmit demand shocks into prices, implying that the price impact of investor demand depends critically on institutional structure. This point is particularly relevant for recent work that uses 13F filings to estimate price multipliers, as 13F-based estimations pool retail-oriented mutual funds with institutional investment vehicles, potentially obscuring substantial differences in how demand shocks translate into price impact. Relatedly, our findings caution against extrapolating the demand effects of mutual funds to the broader institutional landscape. Finally, the effective role of transition managers in mitigating price impact of institutional capital underscores the importance of trading infrastructure in maintaining orderly markets and absorbing large capital allocations without destabilizing prices.

The remainder of the paper proceeds as follows. Section 2 discusses the relation of our work to the existing literature. Section 3 describes the holdings data of separate accounts and other dataset used in the paper. Section 4 compares the price effects of mutual fund and separate account flows through three empirical settings: contemporaneous price impact, fire sales, and flow-induced price fragility. Section 5 examines possible explanations for the divergent price impacts. Section 6 investigates the role of transition managers in suppressing execution costs and price dislocations. Section 7 concludes. Additional results are supplemented in the appendices.

2 Relation to Prior Literature

Our paper contributes to the literature in several ways. First, it relates to the research on the demand effects and asset prices. While traditional asset-pricing frameworks attribute price movements solely to cash-flow and discount-rate variation (Cochrane, 2011), this literature documents that investor demand can have large price effects. Evidence comes from index additions and deletions (e.g., Harris and Gurel, 1986; Shleifer, 1986; Wurgler and Zhuravskaya, 2002; Chang et al., 2015; Pavlova and Sikorskaya, 2023),[8] as well as mutual fund flows (e.g., Teo and Woo, 2004; Coval and Stafford, 2007; Froot and Teo, 2008; Lou, 2012; Ben-David et al., 2022a; Li and Lin, 2025; Huang et al., 2025b). A recent demand-based asset pricing literature estimates price elasticity based on the fund-family level 13F filings that aggregate holdings of mutual funds and various institu-

[8]Greenwood and Sammon (2025) show that the index effect has mostly disappeared in recent years despite the significant increase in index investing.

tional investment vehicles (e.g., Koijen and Yogo, 2019; Gabaix and Koijen, 2021; Koijen et al., 2024). We contribute to this literature by demonstrating substantial heterogeneity in the extent to which investor demand moves prices across different investment vehicles. Strikingly, even flows of different investment vehicles managed under the same investment strategies by the same portfolio managers can have stark differences in price impact.

Our paper is also related to the small but growing literature on institutional investment products. Early notable studies include Busse et al. (2010), Evans and Fahlenbrach (2012), Elton et al. (2014), and Jenkinson et al. (2016). More recently, Gerakos et al. (2021) provides a comprehensive analysis of institutional product performance, while Jones et al. (2022) compares the performance of institutional products with mutual funds. Evans et al. (2022) examine diseconomies of scale in institutional separate accounts employing quantitative or fundamental approaches. Huang et al. (2025a) argue that researchers should include twin institutional investment vehicles in order to reach an accurate measure of scale, and the assets of institutional vehicles meaningfully influence managers' portfolio decisions. We diverge from these studies by emphasizing the stark differences in the price impacts of institutional versus retail investor flows.

Our paper is also among the very few academic studies on transition managers—an important class of intermediaries in institutional investing yet mostly overlooked by academic research. Ang and Madhavan (2024) show that transition managers can execute large-scale transitions with costs closely aligned to pre-trade estimates and even large and complex trades can be executed at modest cost. Obizhaeva (2009), Obizhaeva (2012), and Kyle and Obizhaeva (2016) use transition orders from a major transition manager during 2001 to 2005 to test various market microstructure theories. We extend this literature by documenting the critical role transition managers play in executing institutional demand

and mitigating the price impact of large capital allocations.

3 Data

Our fund sample consists of U.S. domestic equity mutual funds and separate accounts from Morningstar, covering both actively and passively managed strategies. The Morningstar mutual fund database reports returns and characteristics at the share-class level. We aggregate multiple share classes of the same mutual fund into a single fund by taking asset-weighted averages of returns and characteristics, with total fund AUM defined as the sum of AUM across its share classes. Following Chen et al. (2004), Pástor et al. (2015), and others, we include a mutual fund in the sample once its inflation-adjusted AUM exceeds $15 million.[9]

The separate account data in Morningstar is reported by asset management companies at the composite level, where multiple separate accounts following the same investment strategy are aggregated into a single composite. The data are high-quality and reliable.[10] According to Morningstar, a substantial majority—approximately 90%—of the institutional products in the database are managed by firms that comply with Association for Investment Management and Research (AIMR) reporting standards.

[Figure 1 About Here]

Because disclosure is voluntary, coverage of separate accounts is limited prior to 2000. To ensure sufficient representation of institutional products throughout the sample, we begin our analysis in 2001Q4 and end in 2024Q4. Figure 1 plots the total asset under

[9] We follow Pástor et al. (2015) and use U.S. stock market capitalization as the scaling factor to adjust AUM to December 2024 levels.

[10] See Huang et al. (2025a) for a detailed discussion of Morningstar's separate account data.

management of mutual funds and separate accounts in our sample. One can see that the total size of separate accounts is comparable to the mutual fund sector.

We also obtain mutual fund and separate account holdings from Morningstar. Mutual fund holdings are reported at the portfolio level, while separate account holdings are reported at the composite level. To recover composite-level positions for separate accounts, we combine the portfolio weights from the holdings data with each composite's AUM at the corresponding quarter-end.

We use stock price data from CRSP database. Our sample stocks include common stocks (CRSP share code 10 or 11) listed on NYSE, AMEX, and NASDAQ. To be included in the sample, the stock must be held by at least one mutual fund or separate account during the quarter.

[Table 1 About Here]

Table 1 reports the summary statistics for the fund-quarter observations (Panel A) and stock-quarter observations (Panel B) in our sample. One can see that separate accounts (at the composite-level) on average have a smaller AUM, a younger age, and a lower portfolio turnover ratio than mutual funds. Panel B shows that the sample stocks exhibit a large variation in flow-induced trades from both mutual funds and separate accounts, and the detailed construction of these measures is explained the following section.

4 Comparing Flow-induced Price Effects of Separate Accounts and Mutual Funds

In this section, we compare the price impact of flow-induced trading between mutual funds and separate accounts. We begin by documenting that, similar to mutual funds, holdings of separate accounts proportionally increase with capital inflows and decrease with capital outflows. We then assess the price impact of separate account flows across three empirical settings: (1) the price impact of flow-induced trading (Lou, 2012); (2) the price dynamics associated with fire sales (Coval and Stafford, 2007); and (3) flow-induced fragility and the resulting non-fundamental return volatility (Greenwood and Thesmar, 2011). Across all three settings, we find that separate account demand barely moves prices and does not trigger fire-sale dynamics or price fragility.

4.1 Separate account flow-induced demand

To set the stage for measuring flow-induced demand shocks, we first examine how separate account holdings change with respect to institutional capital flows. Prior studies show that mutual fund holdings tend to proportionally change in response to inflows (outflows) (e.g., Lou, 2012), a pattern that allows researchers to construct measures of mutual fund flow-induced demand shocks. In this subsection, we extend this analysis to separate accounts.

We measure quarterly percentage fund flow as the change in total net assets (TNA) after adjusting for portfolio returns:

$$Flow_{i,t} = \frac{TNA_{i,t} - TNA_{i,t-1} \times (1 + Ret_{i,t})}{TNA_{i,t-1}}, \tag{1}$$

where $TNA_{i,t}$ is the total net assets of fund i at quarter t end, and $Ret_{i,t}$ is the fund gross return in quarter t. Fund flows are computed at the mutual fund level or separate account composite level, and quarterly fund flows are winsorized at the 500% level.

We examine flow-induced trading using Fama-MacBeth regressions on the sample of fund-quarter-stock observations, restricting the stock universe to each fund's existing holdings at the beginning of the quarter. The regression specification is:

$$Pct\_Trade_{i,j,t} = \beta_0 + \beta_1 \times Flow_{i,t} + Controls + \varepsilon_{i,j,t}, \quad (2)$$

where $Pct\_Trade_{i,j,t} = Shares_{i,j,t}/Shares_{i.j.t-1} - 1$ is the split-adjusted percentage change in the number of shares of stock j held by fund i in quarter t. $Flow_{i,t}$ is the percentage flow of fund i in the same quarter. The control variables include the lagged ownership of the stock j by fund i as a fraction of shares outstanding, the stock's Amihud illiquidity measure, and the portfolio weight of stock j in fund i. We also interact $Flow_{i,t}$ with each of these stock characteristics. Finally, we split the sample into inflow and outflow subsamples based on the sign of $Flow_{i,t}$, and estimate the regressions separately for each subsample.

[Table 2 About Here]

Table 2 presents the regression results. Columns (1)-(4) report the results for mutual funds. The coefficient estimates on β_1 suggest mutual funds scale up existing holdings by 0.70% in response to a 1% inflow and scale down existing holdings by 0.75% in response to a 1% outflow, consistent with the findings of Lou (2012). Columns (5)-(8) report the results for separate accounts. We find that existing holdings of separate accounts increase by 0.78% with 1% inflow and decrease by 0.93% with 1% outflow. Thus, flows of separate accounts create demand shocks on existing portfolio holdings similar to mutual fund flows. Unlike retail mutual fund investors, however, institutional investors often use transition managers to implement trades associated with large capital allocation, which we will explain in details in Section 6.

4.2 Price impact of separate account flow-induced trading

In this subsection, we analyze the price impact of separate account flow-induced trading (FIT). Motivated by the results in the previous subsection and following Lou (2012), we construct two measures of flow-induced trading that capture the aggregate demand shock exerted on each stock:

$$\text{FIT1}_{j,t} = \frac{\sum_i \text{Shares}_{i,j,t-1} \times \text{Flow}_{i,t} \times \text{PSF}}{\sum_i \text{Shares}_{i,j,t-1}}, \tag{3}$$

and

$$\text{FIT2}_{j,t} = \frac{\sum_i \text{Shares}_{i,j,t-1} \times \text{Flow}_{i,t} \times \text{PSF}}{\text{Shrout}_{\mathrm{j,t-1}}}, \tag{4}$$

where $\text{Shares}_{i,j,t-1}$ is the number of shares of stock j held by fund i at the end of quarter $t-1$, PSF is a partial scaling factor which is empirically close to one,[11] and $\text{Shrout}_{\mathrm{j,t-1}}$ is the number of shares outstanding of stock j at the end of quarter $t-1$. The numerator of both FIT1 and FIT2 aggregates the flow-induced share demand for stock j across all funds. FIT1 scales this aggregate demand by the total number of shares of the stock held by all funds, whereas FIT2 scales the same aggregate flow-induced share demand by the stock's total shares outstanding.[12]

To compare the price impact between mutual funds and separate accounts, we construct FIT measures separately based on mutual fund data and separate account data. Table 1 shows that both mutual fund- and separate account-based FIT measures exhibit substantial variations among stock-quarter observations. In particular, the standard de-

[11] The partial scaling factor captures funds' differential trading behavior in response to inflows and outflows and across stocks with different characteristics (see Table 2). For simplicity, we set PSF to one in our baseline analysis. In the Appendix, we provide robustness checks that allow PSF to differ between inflow- and outflow-induced trading, based on the estimation in Table 2.

[12] As a result, a FIT1 value of 1% suggests that the aggregate fund industry increases its positions in stock j by 1% in response to flows. A FIT2 value of 1% indicates that funds collectively purchase 1% of the stock's shares outstanding in response to flows.

viations of the separate account FIT measures are larger than those of mutual funds, indicating larger variations in demand shocks from separate account flows.

We estimate the price impact of mutual fund and separate account flow-induced trading using Fama–MacBeth regressions at the stock–quarter level over the sample period of 2001Q4–2024Q4. The regression specification is:

$$Ret_{j,t} = \beta_0 + \beta_1 \times FIT_{j,t}^{MF} + \beta_2 \times FIT_{j,t}^{SA} + Controls_{j,t-1} + \varepsilon_{j,t}, \tag{5}$$

where $Ret_{j,t}$ is the return of stock j in quarter t, and the main independent variables are the mutual fund–based and separate account–based FIT measures for the same stock-quarter. The control variables include stock characteristics measured at the previous quarter-end, such as size, book-to-market ratio, past twelve-month return, asset growth, gross profitability, and Amihud illiquidity. We exclude stocks with share prices below $1 at the previous quarter-end to mitigate the influence of penny stocks.

The coefficient estimates of β_1 and β_2 in equation (5) capture the price impact of the flow-induced trading by mutual funds and separate accounts, respectively. Importantly, this regression is estimated only for stock–quarter observations held by both the mutual fund and separate account sectors, ensuring that we are comparing price impacts arising from different investor demands within a common universe of stocks. Panel A of Table 3 reports the results.

[Table 3 About Here]

Using the FIT measure that scales the aggregate demand by the total number of shares held by funds, column (1) shows that a 10% FIT1^{MF} is associated with 2.41% contemporaneous stock returns (t-statistic = 4.54), whereas column (2) shows that FIT1^{SA}

has virtually no price impact. In column (4), when we include both FIT1$^{\text{MF}}$ and FIT1$^{\text{SA}}$ as explanatory variables while controlling for other stock characteristics, the estimated price impacts remain essentially unchanged. Using the FIT2 measure, the results in columns (5)-(8) similarly confirm that only mutual fund flow-induced trading generates a significant price impact. In terms of economic magnitude, column (8) shows that when the aggregate mutual fund sector buys 1% of a stock's shares outstanding in response to flows, the stock experiences a 1.64% contemporaneous price run-up (t-statistic = 5.80). By contrast, the flow-induced price impact from separate accounts is economically negligible and statistically insignificant across specifications.

We next examine the return reversal patterns following flow-induced demand shocks. As mutual fund FIT generates non-fundamental price pressures, we expect these contemporaneous price impacts to reverse in subsequent quarters. In contrast, because separate account FIT produces negligible contemporaneous price movements, no meaningful reversals should follow. In Panel B of Table 3, we estimate Fama-MacBeth regressions of quarterly stock returns on the twelve-quarter average of past FIT$^{\text{MF}}$ and FIT$^{\text{SA}}$. We indeed find a strong reversal associated with past FIT$^{\text{MF}}$, while past FIT$^{\text{SA}}$ displays no reversal pattern. Overall, these results indicate that separate account flow-induced demand is far less price-moving.

4.3 Price dynamics of separate account fire sales

In this subsection, we further examine flow-induced price pressures when funds are experiencing extreme outflows, following the research design of Coval and Stafford (2007). The key idea is that funds facing extreme outflows tend to fire-sell existing holdings, generating significant downward—and largely non-fundamental—price pressures on stocks held in common by distressed funds. We compare the stock price dynamics associated with mutual fund fire sales to those associated with separate account fire sales to assess the differential price impact of the two types of investment vehicles.

We closely follow Coval and Stafford (2007) in implementing the "fire-sale" test. In each quarter t, we classify the bottom 10% of funds by percentage flow as experiencing extreme outflows and the top 10% as experiencing extreme inflows.[13] The actual sales (purchases) of a stock by funds in the extreme-outflow (extreme-inflow) group are defined as fire sales (fire purchases). We then construct a $PRESSURE$ variable for each stock-quarter observation as:

$$PRESSURE_{j,t} = \frac{\sum_i(\max(0, \Delta Shares_{i,j,t})|Flow_{i,t} > Pctl(90th)) - \sum_i(\max(0, -\Delta Shares_{i,j,t})|Flow_{i,t} < Pctl(10th))}{AvgVolume_{j,t-4:t-3}}. \tag{6}$$

Here, the numerator is the difference between aggregate fire purchases and aggregate fire sales for each stock, and we scale this difference by the stock's average quarterly trading volume over quarters $t-4$ to $t-3$. Thus, $PRESSURE_{j,t}$ measures the net fire-sale volume for stock j in quarter t.

Following Coval and Stafford (2007), we define fire-sale stocks in each quarter as those in the bottom decile of the $PRESSURE_{j,t}$ distribution. In particular, fire-sale stocks are identified separately for distressed mutual funds and distressed separate accounts. We find that the sample mean $PRESSURE$ among fire-sale stocks is -0.44% for mutual fund-based fire sales and -0.68% for separate account-based fire sales. Hence, on average, separate account–based fire-sale stocks experience slightly larger flow-induced demand shocks than those associated with mutual fund fire-sales in our sample.

[13] Flow rankings of mutual funds and separate accounts are generated separately within their own pools.

We conduct an event study to examine the cumulative abnormal returns (CARs) associated with fire sales.[14] For each fire-sale stock in each calendar quarter from 2001Q4 to 2024Q4, we track its CAR from one quarter before the fire-sale event quarter to five quarters afterward. We then compute the equal-weighted average CAR across all fire-sale stocks in each event quarter, followed by time-series averaging across calendar quarters to obtain the event-time CARs and their associated t-statistics.

[Figure 2 About Here]

Panel (a) of Figure 2 plots the event-time CAR patterns for mutual fund–based and separate account–based fire sales, and Table 4 reports the corresponding CARs and t-values. For mutual fund fire sales, we observe a pronounced price decline of -2.27% (t-statistic $= -5.82$) through the end of the event quarter.[15] Over the subsequent five quarters, prices gradually recover, and CARs revert toward 0%. This pattern indicates that mutual fund fire sales impose substantial non-fundamental downward pressure on stock prices.

[Table 4 About Here]

For separate account-based fire sales, however, the price decline is much more modest. The CAR through the end of the fire-sale quarter is only -0.57%, and it is statistically indifferent from zero with a t-statistic of -1.24. This stark contrast indicates that fire sales by separate accounts exert far smaller price effects than those prompted by mutual fund distress, despite comparable or even larger underlying demand shocks. These results

[14] Following Coval and Stafford (2007), abnormal returns are computed relative to the equal-weighted average return of stocks held by mutual funds.

[15] Consistent with Coval and Stafford (2007), we also find that the stock prices of fire-sale stocks begin to decline in the quarter preceding the event quarter.

reinforce the finding that separate account flows exert far weaker price pressures than mutual fund flows.

4.4 Flow-induced stock price fragility

Having documented the differential price impacts of mutual fund versus separate account flow-induced trading and fire sales, we now examine their implications for flow-induced price fragility following Greenwood and Thesmar (2011). The underlying intuition is that if flow-induced trading generates non-fundamental price pressures, then variation in such trading should induce non-fundamental volatility in the prices and returns of those stocks. In this sense, an ex-ante measure of expected variation in flow-induced trading—referred to as fragility—should predict a stock's future return volatility.

We follow Greenwood and Thesmar (2011) in constructing mutual fund- and separate account-based measures of fragility as

$$G_{j,t} = {W_{j,t}}' E_t(\Omega_{t+1}) W_{j,t}, \tag{7}$$

where $W'_{j,t} = [w_{1,j,t}, w_{2,j,t}, ..., w_{K,j,t}]$ is the vector of funds' ownership shares in stock j, with $w_{i,j,t} = Shares_{i,j,t}/Shrout_{j,t}$, and $E_t(\Omega_{t+1})$ is the conditional variance-covariance matrix of fund flows in quarter $t+1$. To estimate $E_t(\Omega_{t+1})$, we compute the variance-covariance matrix of fund flows using an eight-quarter rolling window. Following Greenwood and Thesmar (2011), we restrict the computation of fragility to large-cap stocks—those above the NYSE median market capitalization—to keep the matrix operations computationally manageable.[16] As equation (7) makes clear, fragility is jointly determined by a stock's ownership structure and the expected variance–covariance matrix of fund flows: greater

[16] Appendix B provides additional details on the derivation and estimation of the fragility measure.

ownership concentration and more highly correlated fund flows lead to higher stock price fragility.

We estimate the predictive power of fragility using Fama–MacBeth regressions of one-quarter-ahead stock return volatility on mutual fund– and separate account–based fragility:

$$\sigma_{j,t+1} = \beta_0 + \beta_1 \times \sqrt{G_{j,t}}^{MF} + \beta_2 \times \sqrt{G_{j,t}}^{SA} + \sigma_{j,t} + \varepsilon_{j,t+1}, \tag{8}$$

where $\sigma_{j,t+1}$ is the standard deviation of daily stock returns for stock j in quarter $t+1$. $\sqrt{G_{j,t}}^{MF}$ and $\sqrt{G_{j,t}}^{SA}$ are the square roots of mutual fund- and separate account-based fragility, respectively. We control for the lagged volatility to absorb persistence in stock-level volatility.

Table 5 reports the regression results. For example, column (5) reports volatility forecasts by mutual fund-based and separate account-based fragility without controlling for lagged volatility. A 0.67% increase in $\sqrt{G_{j,t}}^{MF}$ (from the 10^{th} to the 90^{th} percentile) predicts a 0.34% increase in daily return volatility (=0.511×0.67%), which is economically large relative to the mean daily return volatility of 2.13% (see Table 1). The coefficient is also highly significant, with a t-statistic of 6.6. By contrast, a 1.39% increase of $\sqrt{G_{j,t}}^{SA}$ (from the 10^{th} to the 90^{th} percentile) predicts only a 0.03% increase in stock return volatility (=0.025×1.39%), and it is not statistically significant. Column (6) further shows that $\sqrt{G_{j,t}}^{MF}$ remains a strong predictor of future volatility after controlling for lagged volatility, whereas $\sqrt{G_{j,t}}^{SA}$ continues to exhibit insignificant predictive power.

[Table 5 About Here]

Overall, these results show that mutual fund flow-induced fragility imposes substantial non-fundamental risks on stocks, whereas the influence of separate account–based fragility is limited. This pattern is fully consistent with our earlier findings on differential flow-induced price impacts, reinforcing the conclusion that separate account flows transmit far weaker demand-driven distortions to asset prices than mutual fund flows.

5 Exploring Some Possible Explanations

In this section, we explore why mutual fund flows move prices while separate account flows do not. We evaluate two possibilities: (*i*) differences in investment strategies between mutual funds and separate accounts, and (*ii*) "liquidity timing" by institutional investors when allocating capital among separate accounts. We find neither of these explanations is supported in the data.

5.1 Analysis based on separate account-mutual fund twins

A potential explanation for our earlier findings is that investment strategies employed by separate accounts differ substantially from those used by mutual funds, giving rise to different capacities to accommodate flows. To test this possibility, we exploit the "twin" setting of mutual fund–separate account pairs.

Specifically, the twins refer to pairs of mutual funds and separate accounts that are managed under same investment strategy by the same portfolio managers. As demonstrated by Huang et al. (2025a), the majority of mutual funds have twin institutional investment vehicles, serving institutional investors. These mutual fund-separate account twins allow us to identify differences in price impact across investor types while holding investment strategy and portfolio management constant.

To implement this analysis, we use the StrategyID provided by Morningstar to link separate accounts and mutual funds that operate under the same investment strategy. We retain only those separate accounts and mutual funds that can be matched to at least one counterpart, and we refer to this subsample as the “twin sample.” We then reconstruct the FIT measures, as described in Section 4.2, using only the funds in the twin sample. Intuitively, FIT^{MF} and FIT^{SA} within this sample represent demand shocks originating from twin vehicles that follow the same strategy and are managed by the same portfolio managers.

Panel A of Table 6 reports the estimated price impacts of FIT^{MF} and FIT^{SA} based on the regression specification of equation (5). Within the twin sample, the price impact of FIT^{MF} remains substantial, whereas the price impact of FIT^{SA} continues to be statistically indistinguishable from zero. For example, column (6) shows that a mutual fund FIT equivalent to 1% of a stock's shares outstanding is associated with a 1.80% contemporaneous price increase (t-statistic = 4.08), while an equivalent separate account FIT moves prices by only 0.02% (t-statistic = 0.08).

[Table 6 About Here]

Additionally, we re-estimate the fire-sale and fragility tests from Sections 4.3 and 4.4 using the twin sample. In Panel (b) of Figure 2, we observe that fire sales by separate accounts with twins generate only mild price declines, whereas fire sales by mutual funds with twins produce sizable and persistent downward price pressures. Table A.1 further shows that fragility induced by separate accounts within the twin sample does not significantly predict future stock return volatility, while mutual fund–induced fragility remains both statistically and economically meaningful.

Taken together, the results in this subsection indicate that differences in investment strategies do not explain the contrasting price impacts of mutual fund and separate account flows.

5.2 Controlling for aggregate market liquidity

Another potential explanation for the differential price impacts is that institutional investors, such as pensions, endowments, and insurance companies, might be better at timing market-wide liquidity when allocating capital among separate accounts. As a result, flows move in and out of separate accounts when the aggregate market liquidity is more favorable.

To test this hypothesis, we use the aggregate market liquidity measure of Pástor and Stambaugh (2003).[17] We split the sample into two equal halves based on the level of market liquidity and re-estimate the price-impact regressions separately within each sub-period. Table 7 reports the estimated price impacts of FIT^{MF} and FIT^{SA} during high- and low-liquidity periods.

[Table 7 About Here]

One can see that FIT^{MF} exerts highly significant price impacts in both high- and low-liquidity periods, with stronger effects when liquidity is low. For example, the price-impact estimate of FIT2^{MF} is 1.91 in the low-liquidity quarters, compared with 1.38 in high-liquidity quarters. In contrast, the price-impact estimates of FIT^{SA} are insignificant in both low- and high-liquidity periods.

Additionally, Appendix Figure A.1 illustrates the fire-sale CAR patterns across high- and low-liquidity periods. In both environments, mutual fund fire sales generate substantially larger downward price pressures than separate account fire sales. Appendix Table A.2 further reports volatility forecasts based on fragility in the two sub-periods. Mutual

[17] We thank Robert Stambaugh for making this dataset publicly available: `https://finance.wharton.upenn.edu/~stambaug/`. We use the "level of aggregate liquidity" series shown in Figure 1 of Pástor and Stambaugh (2003).

fund flow-induced fragility significantly predicts future volatility under both high- and low-liquidity conditions, whereas the effect of separate account–based fragility remains muted in each case.

In summary, these findings indicate that the differential price impacts of mutual fund and separate account flows hold under different market-wide liquidity conditions.

6 Institutional Capital Allocation and Transition Managers

Having ruled out some alternative explanations, in this section, we examine the role of transition managers—specialized intermediaries that frequently execute portfolio allocations on behalf of institutional investors. Our evidence suggests that transition managers substantially reduce execution costs and help prevent flow-induced price dislocations.

6.1 Background on transition managers

Transition managers are specialized intermediaries responsible for executing large portfolio allocations for institutional investors, with the primary objective of minimizing transaction costs—often referred to as implementation shortfall. The transition management industry emerged in the late 1980s and early 1990s. Russell Investments is widely recognized as a global leader, and major providers such as State Street Corporation, Citi, and Northern Trust Corporation have also operated in this space for more than 30 years. These firms provide dedicated infrastructure—multi-venue trading platforms, execution desks, derivative overlay tools, and comprehensive reporting—that enables institutions to carry out sizable capital allocations efficiently.

A typical portfolio transition follows a structured sequence. First, the incoming manager is notified several days in advance of the sponsor's intention to allocate assets. Next, the outgoing manager is informed—typically one to two days before the transition—of the upcoming withdrawal. To reduce information leakage and prevent front-running, the outgoing manager is instructed to cease trading and to submit a certified holdings file. Immediately prior to the transition, the transition manager receives the verified legacy portfolio along with the target holdings specified by the incoming manager. Using these inputs, the transition manager designs and executes the reallocation from the old to the new portfolio. Upon completion, the transition manager delivers a detailed post-trade report summarizing execution costs, trading strategy, and realized outcomes. Figure 3 illustrates the process of transition trades.

[Figure 3 About Here]

Based on market participants (e.g., Bagley and Kothare, 2014; Meketa Investment Group, 2019), transition management can significantly mitigate price impact in a few ways. First, transition managers trade across a wide range of execution venues to access liquidity while minimizing signaling. Rather than routing large directional orders to public order books, they strategically allocate flow to dark pools, conditional block venues, crossing networks, and closing auctions. They complement these with principal or risk-transfer trades when appropriate. The ability to fragment orders across venues, each with different liquidity and transparency properties, allows transition managers to reduce the market footprint of large trades and avoid the price slippage associated with concentrated execution.

Second, transition managers benefit from scale and network externalities that expand the effective supply of liquidity. Because they intermediate a continuous flow of transitions across clients, they frequently observe natural offsets—buyers in one mandate matched with sellers in another—which allows them to internalize liquidity and reduce the amount of risk sent to the open market. Their long-standing relationships with broker-dealers, electronic liquidity providers, and crossing platforms further widen the set of counterparties willing to supply liquidity. These institutional connections and flow-aggregation advantages enable transition managers to absorb large trades with far less reliance on public depth, thereby materially reducing price impact.

Third, transition managers are cautious about information leakage, which is a driver of both temporary and permanent price effects. Large reallocations are often predictable and easily identified by liquidity suppliers, leading to anticipatory quoting and adverse price drift. Transition managers suppress this informational footprint by controlling the dissemination of trade lists and using derivative overlays to neutralize market exposures before trading cash securities. These practices reduce the extent to which counterparties can infer the direction or magnitude of the underlying transition, lowering the market's incentive to adjust prices against the order.

In contrast, mutual funds are structurally obligated to prioritize daily liquidity over minimizing execution costs, as the rigid Net Asset Value (NAV) pricing rule mechanically forces managers to trade to accommodate daily investor subscriptions and redemptions. Because mutual flows are uncertain and often confirmed late in the day, mutual fund managers face intense time pressure to execute promptly, risking either cash drag or tracking error, which severely limits their scope to optimally source liquidity.[18] Compounding this, mutual fund trades are typically routed through broker-dealers who rely heavily on displayed liquidity and execution algorithms that prioritize timely completion over infor-

[18] A mutual fund manager's knowledge of client flows varies depending on the platform used by investors. For some platforms, mutual fund managers may learn about client purchases or sales as late as the next morning (Wahal and Wang, 2022).

mation suppression. This reliance on visible liquidity can expose mutual fund trades to information leakage, leading to higher implicit trading costs.

6.2 Estimating price impact of transition trades

In this subsection, we analyze the price impact of U.S. equity transition trades using novel trade-level data from a leading transition manager. Consistent with the main findings in Section 4, we find that these trades executed by the transition manager generate statistically insignificant and economically negligible price impact.

The dataset comprises 1,787 distinct transition programs executed between 2013 and 2021. Each transition program moves a legacy portfolio to a target portfolio or move capital from or into cash (also known as "one-sided events"). Table 8 reports summary statistics for these programs. The average transition program involves \$248 million in traded value of U.S. public equities, spans 578 individual trades, and covers 237 distinct stocks. Transitions are typically executed over a short horizon: 31.45% of programs are completed within a single day, and 60.16% are completed within five days.

[Table 8 About Here]

We proceed to analyze the cost of transition trades. Consistent with the main findings in Section 4, we find that these trades executed by the transition manager generate statistically insignificant and economically negligible price impact. Specifically, we measure trading costs as the difference between the trade execution price and a benchmark price:

$$TradeCost = D \times \frac{Price - BenchmarkPrice}{BenchmarkPrice}, \tag{9}$$

where $Price$ is the execution price of the trade and D denotes the trade direction, equal to 1 for buys and -1 for sells. We use two benchmark prices: (i) the previous day's closing price, and (*ii*) the same day's opening price. This transaction-cost measure captures implicit trading costs—including price impact and bid–ask spread components—but excludes explicit costs such as commissions.[19]

With this cost measure, we estimate a cross-sectional regression of trade-level transaction costs on trade- and transition-program-level characteristics:

$$TradeCost_{j,p,t} = \alpha + \beta_1 TradeSize_{j,p,t} + Controls + \epsilon_{j,p,t}, \tag{10}$$

where $TradeCost_{j,p,t}$ is the implicit cost per trade dollar for stock j executed in transition program p at time t, and $TradeSize_{j,p,t}$ is the trade's dollar volume expressed as a fraction of the stock's same-day dollar trading volume from CRSP. The control variables include stock- and program-level characteristics: the log of market capitalization, idiosyncratic volatility, Amihud illiquidity, daily turnover, the inverse of stock price, a NASDAQ indicator, and the total dollar trading volume of the transition program.

To compare directly with the evidence of mutual fund trading in Busse et al. (2021), we estimate the regression coefficients using a Fama–MacBeth procedure. Specifically, we pool all trades within each calendar month and run a cross-sectional regression, then compute the time-series averages of the monthly coefficient estimates and their associated t-statistics. Table 9 reports the results.

[Table 9 About Here]

Across all specifications, we find $TradeSize$ is positively but insignificantly associated with $TradeCost$. For example, column (1) indicates an estimated β_1 of 0.01 (t-statistic = 1.28) when the previous day's close is used as the benchmark. Similar patterns emerge

[19] Based on our conversations with the transition manager, commissions are negligible.

when using the same-day opening price as the benchmark or when estimating costs separately for buy and sell trades. For comparison, Busse et al. (2021) estimates a similar regression for mutual fund trades and obtains a β_1 of 0.811 with a t-statistic of 7.84. Taken together, these results confirm that the price impact of transition trades is negligible relative to mutual funds.

6.3 Comparing transaction costs of transition programs and mutual funds

We further compare the total transaction costs of each transition program with those of mutual funds. For each transition program p, we compute the volume-weighted or equal-weighted average trading cost, as defined in equation (9), across all trades in the program. We then sort all transition programs in our sample into quintiles based on total trading volume and report the average program-level trading cost within each quintile. Table 10 presents the results.

[Table 10 About Here]

When we use the previous close price as the benchmark for trade costs, the program-level average trade cost ranges from 4 to 11 bps, with the smallest programs averaging 11 bps and the largest programs averaging 6 bps. When we use the current-day open price as the benchmark, the program average trade costs range between 7 and 15 bps. In addition, the estimates of program average trade costs are similar if we compute the equal-weighted average trade cost across all trades of each program.

Our estimates are broadly consistent with Ang and Madhavan (2024), the only other study of transition programs, to the best of our knowledge. Ang and Madhavan (2024) analyzes transaction costs of portfolio transitions executed between 2016 and 2023 from a major transition manager. For the 1,058 transition trades of U.S. equity portfolios, Ang and Madhavan (2024) estimates per dollar implicit transition costs due to price impact to be about 12 bps, similar to our estimated per dollar cost of 4 to 11 bps (7 to 15 bps relative to the current-day open price).[20]

These magnitudes of transaction costs are substantially lower than those observed for mutual funds. For example, Edelen et al. (2013) estimate that an average trading volume of 177% of mutual fund positions generates total costs of 144 bps, with 94 bps attributed to price impact. Busse et al. (2021) estimate that with an average turnover rate of 98%, mutual fund trades incur total transaction costs of 75.1 to 101.4 bps, with 47 to 73.5 bps arising from price impact.

In summary, these results suggest that transaction costs for separate account transitions are only about 10% to 20% of those borne by mutual funds, indicating that transition managers are highly effective in minimizing costs associated with institutional capital allocations.

6.4 Additional evidence on transition management

In this subsection, we provide evidence that transition management service is more likely to be used by institutional investors when capital allocations across separate accounts are larger. Because our data only covers transition programs executed by a single transition manager, we interpret the results in this subsection as suggestive.

Consistent with Section 4.3, we use a similar definition of fire-sale events to identify episodes of large-scale capital allocation. Specifically, a fund-quarter observation is classified as a fire sale if its quarterly flow falls below the 10th percentile of quarterly flows

[20] Ang and Madhavan (2024) reports the round-trip implicit costs to be 24 bps, mapping to a per dollar cost of 12 bps.

in the full sample.[21] Each quarter, we compute the number of separate-account fire-sale events as a fraction of the number of existing separate accounts and denote this measure *SA_FireSale%*. We also compute the number of sales-oriented transition programs executed by our transition manager in that quarter, scaled by the number of existing separate accounts, and denote this measure *Transit_Program%*.[22]

We then estimate a time-series regression of *Transit_Program%* on contemporaneous *SA_FireSale%*, controlling for contemporaneous market liquidity and market returns, as well as one-quarter-lagged *Transit_Program%*. Panel A of Table 11 reports the regression results. We find that separate-account fire sales are positively and statistically significantly associated with the incidence of transition programs. By contrast, the association is indistinguishable from zero for mutual-fund fire-sale events.

[Table 11 About Here]

To provide additional evidence on transition-manager use at the individual separate-account level, we match transition programs to separate account–quarter observations in our sample. Because we do not observe the identities of transition-program clients, the matching is necessarily "fuzzy" and relies on overlap in stock holdings and the magnitude of capital flows associated with the transition. We also note that Morningstar reports separate-account data at the composite level—aggregating multiple accounts that follow the same investment strategy into a single composite—which further complicates matching transition programs to separate accounts.

[21] We define fire-sale events for separate accounts and mutual funds separately using their respective full-sample flow breakpoints.

[22] Sales-oriented transition programs are defined as transition programs in which more than 50% of the dollar trading volume is from sales of stocks. Among the 1787 transition programs in our data, 64.4% are sales-oriented programs. The results are robust to alternative cutoff values for defining sales-oriented transition programs.

Using the conservative matching procedure described in Appendix Section C, we are able to match 114 transition programs to 183 separate account-quarter observations.[23] We then examine flows in the matched separate account–quarter observations to assess how separate-account flows relate to the use of transition management. To be consistent with the previous analysis, we focus on sales-oriented transition programs here.

Panel B of Table 11 shows that, when we define extreme flow events using the quarter-specific 10th-percentile (5th-percentile) flow cutoff, the incidence of such events among matched separate-account quarters is 34.34% (22.22%), significantly higher than the full-sample benchmark of 10% (5%). In addition, among matched separate-account quarters, the median quarterly percentage flow is −5.73%, significantly lower than the full-sample median of −0.39%. While these results are suggestive because we observe programs from only one transition manager, they are collectively consistent with transition management being more likely to be used for large capital allocation episodes, in line with industry reports (Bagley and Kothare, 2014; Meketa Investment Group, 2019).

We also note that although transition managers contribute significantly to the sharp contrast of flow-induced price impact between mutual funds and separate accounts, they might not be the only reason. Even institutional investors do not use transition management services, asset managers may give institutional clients preferential treatment and execute their flows more carefully. To the extent that such choices dampen price pressure, part of the contrast in price impact may reflect differences in trading and execution quality of asset managers. Rather than weakening our interpretation, these alternative channels also reinforce our broader conclusion that investor demand transmits to prices

[23] Among the 114 matched transition programs, 69 are two-sided programs, which involve an outflow from one separate account and a corresponding inflow to another separate account as part of the transition process.

in highly heterogeneous ways: not all flows are equally “price-moving.”

7 Concluding Discussion

This paper provides new evidence on how institutional flows influence asset prices by studying separate accounts—the dominant investment vehicle for institutional investors and a sector comparable in size to the mutual fund industry. We document a striking contrast between mutual funds and separate accounts: while mutual fund flows generate substantial price impact, amplify price fragility, and trigger fire-sale dynamics, separate account flows exhibit negligible price effects. We show that the differences are not driven by investment strategies in that we observe similar results within mutual fund–separate account twins that are managed under identical strategies by the same portfolio managers. In addition, the contrast persists after controlling for market-wide liquidity condition at the time flows occur, suggesting it is not driven by superior “liquidity timing” of institutional investors when allocating capital among separate accounts.

Our study suggests the important and effective roles of transition managers in mitigating price impact, who often execute capital allocation for institutional investors. Specifically, by examining detailed trade-level data from a leading transition manager, we estimate that price impact and transaction costs of transition trades are about 10% to 20% of mutual fund trades and confirm that transition managers substantially reduce the flow-induced price dislocations.

Our results have several important implications to the large literature that examines investor demand and asset prices. First, they highlight significant heterogeneity in how different investment vehicles transmit demand shocks into prices, suggesting that the price impact of investor flows depends critically on institutional structure and trading technology. Strikingly, even flows of investment vehicles following the same investment strategies can influence prices very differently. Relatedly, our findings caution against generalizing the demand effects of mutual funds to the broader institutional landscape: not all investor demand is equally “price-moving.” Finally, the effective role of transition managers underscores the importance of trading infrastructure in maintaining orderly markets and absorbing large capital allocations without destabilizing prices.

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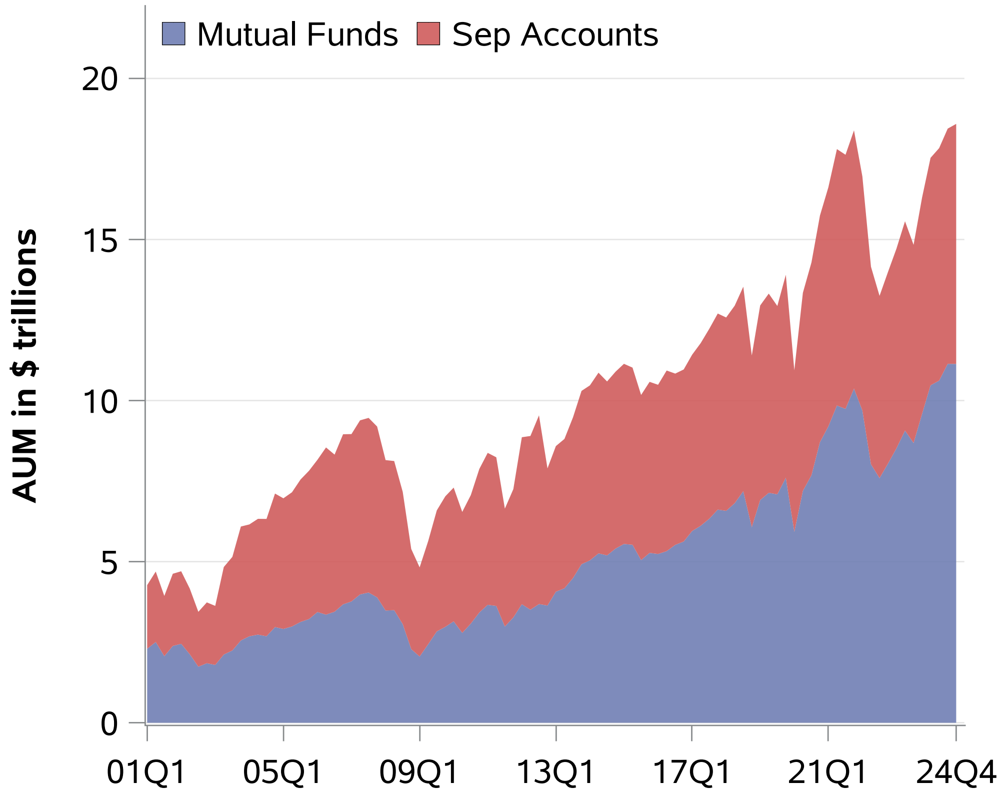
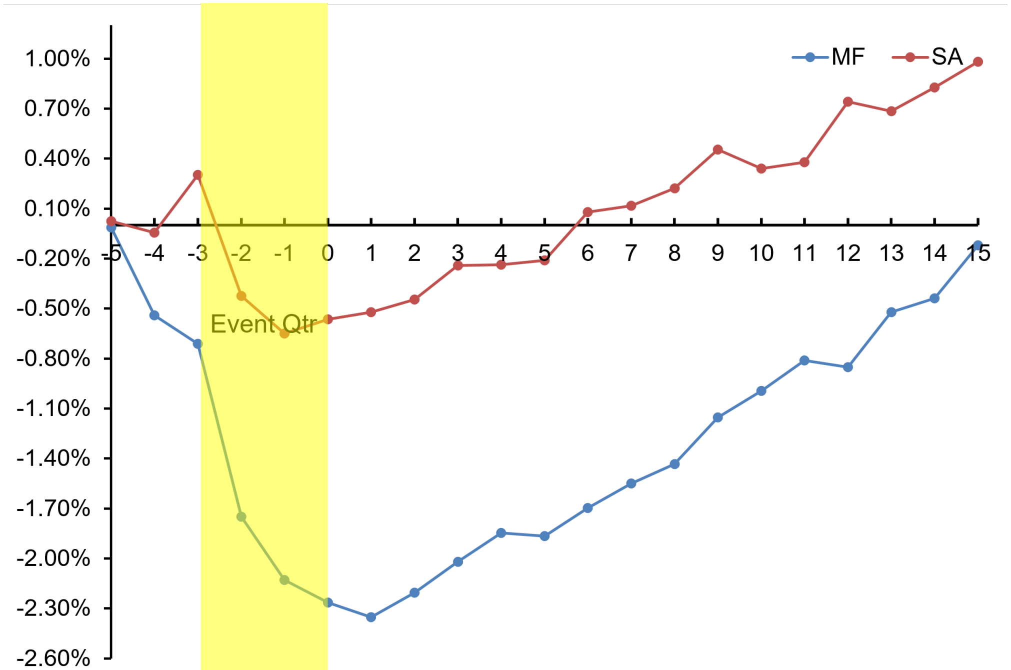
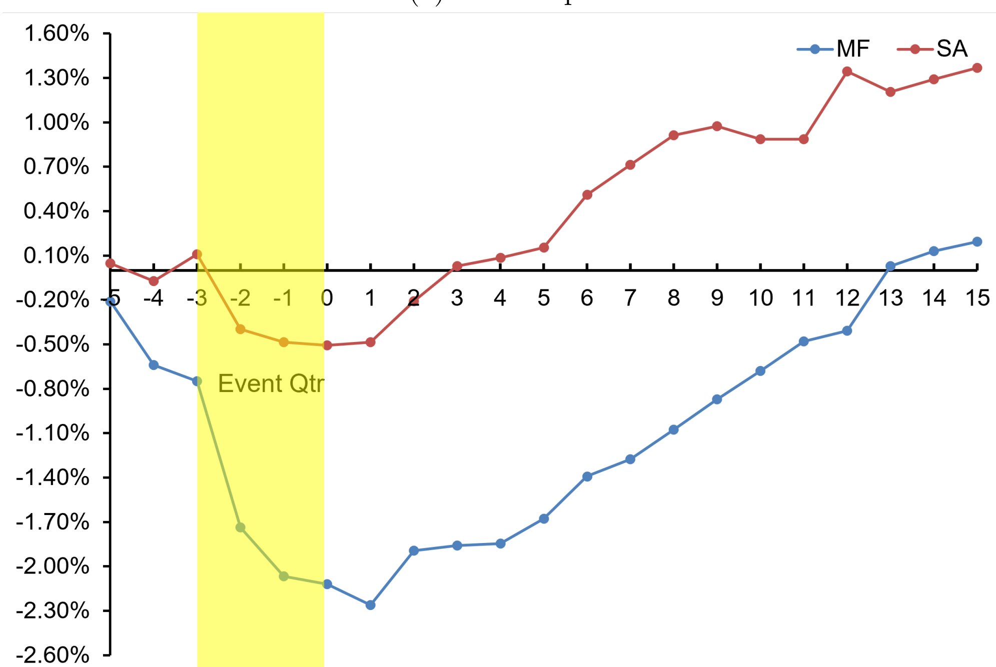


Figure 1: **Total assets of mutual funds and separate accounts.** This figure plots total assets (in $ trillions) of US equity mutual funds and separate accounts at each quarter-end from 2001.Q1 to 2024.Q4.



(a) Full sample



(b) Twin fund sample

Figure 2: **Fire sale event CAR.** This figure plots the event-time cumulative abnormal returns (CAR) associated with mutual fund fire sale and separate account fire sale events during 2001.Q4-2024.Q4. In each calendar quarter, we define stocks under fire sale as the bottom 10% of stocks with the lowest *Pressure*. Then we track the average CAR of fire-sale stocks from one quarter before the fire sale to five quarters after. CAR is computed based on DGTW-adjusted returns. The horizontal axis indicates the event month, where months -2, -1, and 0 belong to the fire sale event quarter. The vertical axis indicates CAR. Panel (a) is based on the full sample of funds; Panel (b) is based on funds with twin vehicles.

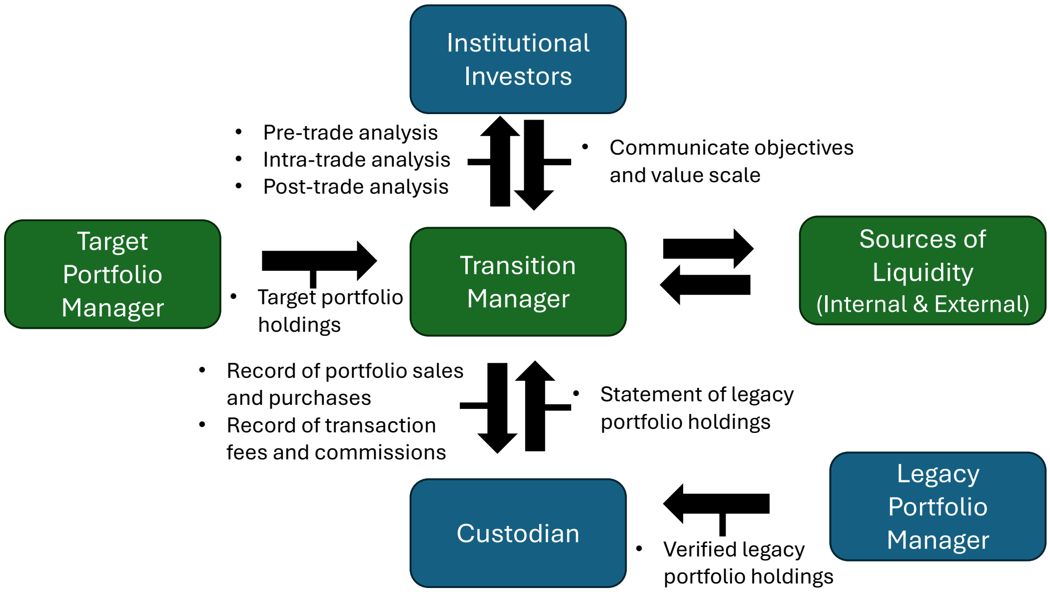


Figure 3: **The process of transition management.**

Table 1: **Summary Statistics.** Panel A reports summary statistics of mutual funds and separate accounts (composite) at fund-quarter observations from 2001Q4 to 2024Q4, Pct_Flow is the quarterly percentage fund flow defined in equation 1. Flow_Vol is the past eight-quarter rolling standard deviation of Pct_Flow. Flow_AR(1) is the first-order autocorrelation of Pct_Flow in the past eight quarters. Turnover is the self-reported annual portfolio turnover ratio. Cash is the percent of portfolio holdings allocated to cash. Panel B reports the summary statistics of stock-quarter observations. NYSE Size Pctl is the stock's size percentile ranking among NYSE stocks. FITs are a set of measures of flow-induced trading, as defined in Section 4.2. The superscript MF (SA) indicates a mutual fund- (separate account-) based FIT measure. σ is the standard deviation of daily stock return in a quarter. Pressures are a set of fire-sale pressure measures, as defined in Section 4.3. $\sqrt{\text{G}}$ is the square root of fragility as defined in Section 4.4.

Panel A: Fund-Quarter Observations

	Mean	STD	P10	P25	P50	P75	P90
Mutual Funds:							
Total Assets ($mi)	2028.30	14905.59	18.16	61.42	257.76	1028.86	3311.01
Gross Return (Qtr)	0.03	0.10	−0.10	−0.02	0.04	0.08	0.13
Age (yr)	15.18	12.98	2.75	6.00	12.17	20.67	29.83
Pct_Flow	0.02	0.30	−0.09	−0.05	−0.02	0.02	0.12
Flow_Vol	0.12	0.25	0.01	0.02	0.05	0.10	0.23
Flow_AR(1)	0.09	0.39	−0.40	−0.19	0.07	0.37	0.62
Turnover (%)	79.14	139.50	12.00	25.80	51.00	91.00	151.00
Cash (%)	2.82	12.68	0.00	0.54	1.77	3.78	6.87
Sep Accounts (Composite):							
Total Assets ($mi)	1374.96	8164.50	1.60	16.96	127.72	688.80	2428.40
Gross Return (Qtr)	0.03	0.10	−0.09	−0.01	0.04	0.08	0.13
Age (yr)	11.18	9.25	1.50	4.17	9.17	16.33	23.67
Pct_Flow	0.06	0.53	−0.12	−0.04	0.00	0.03	0.17
Flow_Vol	0.25	0.44	0.02	0.04	0.09	0.22	0.56
Flow_AR(1)	−0.07	0.37	−0.51	−0.31	−0.11	0.15	0.44
Turnover (%)	60.05	168.05	11.93	22.15	40.13	73.58	118.00
Cash (%)	2.89	7.58	0.00	0.34	1.70	3.56	6.34

Table 1 Continued

Panel B: Stock-Quarter Observations							
	Mean	STD	P10	P25	P50	P75	P90
NYSE Size Pctl (%)	28.02	29.16	0.39	3.03	16.47	47.29	77.03
Return (Qtr, %)	3.20	35.47	−28.57	−11.79	1.14	14.01	31.78
$\mathrm{FIT1}^{\mathrm{MF}}$ (%)	0.49	7.29	−2.92	−1.59	−0.35	1.36	4.01
$\mathrm{FIT1}^{\mathrm{SA}}$ (%)	−0.34	14.44	−6.08	−3.13	−1.15	1.04	4.80
$\mathrm{FIT2}^{\mathrm{MF}}$ (%)	−0.04	0.60	−0.55	−0.24	−0.02	0.08	0.40
$\mathrm{FIT2}^{\mathrm{SA}}$ (%)	−0.17	3.70	−0.67	−0.28	−0.03	0.02	0.24
σ (%)	2.13	1.27	1.04	1.33	1.80	2.52	3.57
$\sqrt{\mathrm{G}}^{\mathrm{MF}}$ (%)	0.40	0.38	0.11	0.18	0.30	0.50	0.78
$\sqrt{\mathrm{G}}^{\mathrm{SA}}$ (%)	0.74	1.52	0.09	0.18	0.36	0.73	1.48
$\mathrm{Pressure}^{\mathrm{MF}}$ (%)	−0.03	1.10	−0.13	−0.04	−0.01	0.00	0.05
$\mathrm{Pressure}^{\mathrm{SA}}$ (%)	−0.07	1.97	−0.19	−0.07	−0.02	0.00	0.04

Table 2: **Fund Holding Position Changes in Response to Flows.** This table reports results from Fama-MacBeth regressions. The unit of observation is fund-quarter-holding stock, and the sample period is 2001Q4-2024Q4. The sample includes only each fund's holdings at the beginning of each quarter; new positions established during the quarter are excluded. The dependent variable is the fund percentage position change on a holding stock in the quarter ($= Shares_{i,j,t}/Shares_{i.j.t-1} - 1$), and the key independent variable is the fund's percentage flow in the quarter. We control for holding stock characteristics at previous quarter-end: Own is the fund's ownership on the holding stock; illiq is the holding stock's Amihud illiquidity measure (in 10^8); Weight is the holding stock's weight in the fund portfolio. The sample is split into inflow and outflow samples based on the sign of fund flow in the quarter; we perform regressions in the two samples separately. t-statistics in parentheses are calculated based on standard errors with Newey-West correction of four lags. *, **, *** indicate significance at the 10%, 5%, and 1% level, respectively.

	Mutual Funds				Separate Accounts			
	Inflow		Outflow		Inflow		Outflow	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Flow	0.700***	0.704***	0.748***	0.704***	0.784***	0.724***	0.934***	0.947***
	(16.40)	(15.73)	(16.90)	(14.57)	(57.70)	(38.31)	(77.34)	(63.36)
Flow×Own		−55.969***		25.519***		2.087		5.753***
		(−5.19)		(6.62)		(0.70)		(4.42)
Flow×illiq		−0.002		−0.000		−0.013***		−0.011**
		(−1.40)		(−0.03)		(−3.74)		(−2.56)
Flow×Weight		2.148		2.057		4.893***		−2.655***
		(1.33)		(1.34)		(9.36)		(−4.73)
Own		−1.640***		−1.055***		−0.184		−0.194
		(−4.41)		(−6.64)		(−0.67)		(−1.09)
illiq		0.000*		0.000		−0.002**		−0.001
		(1.68)		(0.14)		(−2.20)		(−1.64)
Weight		−4.851***		−4.192***		−3.090***		−2.886***
		(−15.14)		(−15.18)		(−8.37)		(−9.71)
No. Obs.	12,047,784	12,047,784	15,451,947	15,451,947	4,158,025	4,158,025	7,371,680	7,371,680
Adj. R^2	0.096	0.102	0.006	0.01	0.341	0.347	0.043	0.046

Table 3: **Price Impact of Flow-induced-trading.** This table reports results from Fama-MacBeth regressions. The unit of observation is stock-quarter, and the sample period is 2001Q4-2024Q4. The dependent variable is quarterly stock returns. Panel A reports the contemporaneous relation between stock returns and flow-induced trading. The key independent variables are flow-induced-trading by mutual funds ($\mathrm{FIT}^{\mathrm{MF}}$) and separate accounts ($\mathrm{FIT}^{\mathrm{SA}}$) in the same quarter. Control variables include stock size, book-to-market ratio (BM), past 12-month returns skipping the most recent month (MOM), asset growth (AG), gross profitability (GP), and Amihud illiquidity (Illiq). We use FIT1 measure in columns (1)-(4) and FIT2 measure in columns (5)-(8). Panel B reports the reversal effect of flow-induced trading. The key independent variables are past 12-quarter average FIT by mutual funds ($\mathrm{PastFIT}^{\mathrm{MF}}_{\mathrm{t-12:t-1}}$) and separate accounts ($\mathrm{PastFIT}^{\mathrm{SA}}_{\mathrm{t-12:t-1}}$). t-statistics in parentheses are calculated based on standard errors with Newey-West correction of four lags. *, **, *** indicate significance at the 10%, 5%, and 1% level, respectively.

Panel A: Contemporaneous Price Impact of FIT

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	FIT Measure 1				FIT Measure 2			
$\mathrm{FIT}^{\mathrm{MF}}$	0.241***		0.244***	0.245***	1.406***		1.573***	1.642***
	(4.54)		(5.20)	(6.05)	(3.19)		(4.09)	(5.80)
$\mathrm{FIT}^{\mathrm{SA}}$		−0.004	−0.012	0.004		−0.157	−0.371	−0.190
		(−0.19)	(−0.63)	(0.30)		(−0.56)	(−1.65)	(−1.03)
Size				0.001				0.001
				(0.37)				(0.37)
BM				0.011**				0.011**
				(2.34)				(2.34)
MOM				0.003				0.003
				(0.39)				(0.34)
AG				−0.005**				−0.005**
				(−2.12)				(−2.12)
GP				0.028***				0.028***
				(4.32)				(4.33)
Illiq				−1257.00				−714.38
				(−0.40)				(−0.24)
No. Obs.	316,515	316,515	316,515	316,515	316,515	316,515	316,515	316,515
Adj. R^2	0.0035	0.0007	0.0042	0.0332	0.0041	0.0008	0.0046	0.0334

Table 3 Continued

Panel B: Reversals of FIT								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	FIT Measure 1				FIT Measure 2			
$\text{PastFIT}^{\text{MF}}_{t-12:t-1}$	−0.195**		−0.186**	−0.120*	−1.948**		−1.799**	−1.385**
	(−2.38)		(−2.18)	(−1.76)	(−2.19)		(−2.04)	(−2.22)
$\text{PastFIT}^{\text{SA}}_{t-12:t-1}$		−0.026	−0.018	0.002		−0.214	−0.1084	−0.159
		(−0.78)	(−0.52)	(0.07)		(−0.71)	(−0.32)	(−0.61)
Size				0.000				−0.000
				(0.10)				(−0.08)
BM				0.010**				0.010**
				(2.27)				(2.26)
MOM				0.003				0.003
				(0.40)				(0.38)
AG				−0.005**				−0.005**
				(−2.11)				(−2.11)
GP				0.026***				0.026***
				(4.15)				(4.14)
Illiq				−1057.10				−705.96
				(−0.35)				(−0.23)
No. Obs.	314,559	311,613	311,307	311,307	314,559	311,513	311,265	311,265
Adj. R^2	0.0014	0.0007	0.0021	0.0326	0.0027	0.0008	0.0034	0.0327

Table 4: **Fire-Sale Event CAR.** This table reports the event-time cumulative abnormal returns (CAR) associated with mutual fund fire sale and separate account fire sale events during 2001Q4-2024Q4. The test design follows Coval and Stafford (2007). In each calendar quarter, we define stocks under fire sale as the bottom 10% of stocks with the lowest *Pressure* from mutual funds or separate accounts (see Section 4.3 for definition). We then track the average event-time CAR for fire-sale stocks from one quarter before the fire-sale quarter to five quarters thereafter. Finally, we compute the time-series average event-time CAR and the associated t-values across the calendar quarters. The CAR is reported for each event month, where months -2, -1, and 0 belong to the fire-sale event quarter. The benchmark returns for CAR calculation are the equal-weighted average returns of stocks held by mutual funds at each time point.

	Mutual Funds		Separate Accounts	
Event Month	CAR	t-value	CAR	t-value
−5	−0.01%	−0.07	0.02%	0.12
−4	−0.54%	−2.04	−0.05%	−0.15
−3	−0.71%	−2.39	0.30%	0.85
−2	−1.75%	−5.96	−0.42%	−1.12
−1	−2.13%	−6.21	−0.65%	−1.60
0	−2.27%	−5.82	−0.57%	−1.24
1	−2.35%	−5.83	−0.52%	−1.03
2	−2.21%	−5.17	−0.45%	−0.78
3	−2.02%	−4.39	−0.24%	−0.39
4	−1.85%	−3.66	−0.24%	−0.35
5	−1.87%	−3.48	−0.21%	−0.30
6	−1.70%	−3.04	0.08%	0.11
7	−1.55%	−2.45	0.12%	0.16
8	−1.43%	−2.11	0.22%	0.30
9	−1.15%	−1.66	0.45%	0.57
10	−1.00%	−1.32	0.34%	0.42
11	−0.81%	−1.06	0.38%	0.49
12	−0.85%	−1.08	0.74%	0.93
13	−0.52%	−0.64	0.68%	0.84
14	−0.44%	−0.51	0.83%	1.01
15	−0.12%	−0.14	0.98%	1.19

Table 5: **Predict Stock Volatility by Fragility.** This table reports the Fama-MacBeth regressions of one-quarter-ahead stock return volatility (σ_{t+1}) on the square root of mutual fund fragility ($\sqrt{G_t}^{MF}$) and separate account fragility ($\sqrt{G_t}^{SA}$). The sample period is from 2002Q1 to 2024Q4, and the sample stocks include stocks with market capitalization above the NYSE median in each quarter. σ_{t+1} is the standard deviation of daily stock returns in quarter $t+1$, and $\sqrt{G_t}$ is the square root of fragility defined in Section 4.4. The control variable is the stock return volatility in quarter t. t-statistics in parentheses are calculated based on standard errors with Newey-West correction of four lags. *, **, *** indicate significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
$\sqrt{\mathrm{G_t}}^{\mathrm{MF}}$	0.530***	0.194***			0.511***	0.188***
	(7.727)	(6.686)			(6.622)	(5.874)
$\sqrt{\mathrm{G_t}}^{\mathrm{SA}}$			0.078***	0.025***	0.025	0.008
			(5.561)	(3.918)	(1.659)	(1.053)
σ_t		0.724***		0.735***		0.724***
		(35.758)		(37.051)		(35.646)
No. Obs	84,957	84,957	84,957	84,957	84,957	84,957
Adj. R^2	0.037	0.509	0.005	0.504	0.04	0.509

Table 6: **Price Impacts of Twin Funds.** Results in this table are based on mutual funds or separate accounts with twin vehicles. Panel A reports the estimation of the price impact of FIT following the test specification in Table 3. Panel B reports the results of predicting stock return volatility by fragility, following the test specification in Table 5. *, **, *** indicate significance at the 10%, 5%, and 1% level, respectively.

Panel A: Price impacts of FIT

	(1)	(2)	(3)	(4)	(5)	(6)
	FIT Measure 1			FIT Measure 2		
FIT^{MF}	0.118***		0.108***	1.747***		1.802***
	(5.75)		(5.00)	(3.52)		(4.08)
FIT^{SA}		0.022	0.008		0.563	0.021
		(1.64)	(0.78)		(1.61)	(0.08)
Size			−0.000			0.000
			(−0.03)			(0.04)
BM			0.007			0.007
			(1.33)			(1.32)
MOM			−0.000			−0.001
			(−0.04)			(−0.08)
AG			−0.004*			−0.004*
			(−1.73)			(−1.76)
GP			0.025***			0.025***
			(3.31)			(3.36)
Illiq			5173.92			5161.83
			(0.73)			(0.75)
No. Obs.	264,179	264,179	264,179	264,179	264,179	264,179
Adj. R^2	0.0024	0.0008	0.039	0.0027	0.0009	0.0389

Panel B: Predict volatility by fragility

	(1)	(2)	(3)	(4)	(5)	(6)
$\sqrt{\text{G}_\text{t}}^{\text{MF}}$	0.462***	0.183***			0.443***	0.174***
	(6.913)	(6.720)			(6.382)	(6.026)
$\sqrt{\text{G}_\text{t}}^{\text{SA}}$			0.087***	0.028***	0.045**	0.014
			(3.989)	(2.722)	(2.350)	(1.328)
σ_t		0.731***		0.735***		0.731***
		(37.022)		(36.956)		(36.901)
No. Obs	84,128	84,128	84,128	84,128	84,128	84,128
Adj. R^2	0.015	0.505	0.003	0.503	0.016	0.505

Table 7: **Market Liquidity and Price Impacts of FIT.** This table reports the price impact of flow-induced trading in subsamples classified by market liquidity. We use the market liquidity measure from Pástor and Stambaugh (2003) to split the sample period of 2001Q4-2024Q4 into two halves. Within each subsample, we re-perform the Fama-MacBeth regressions as in Table 3. *, **, *** indicate significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)
	FIT Measure 1		FIT Measure 2	
Mkt Liquidity:	Low	High	Low	High
FIT^{MF}	0.2616***	0.2282***	1.9130***	1.3768***
	(3.42)	(3.22)	(4.42)	(3.24)
FIT^{SA}	0.0232	−0.0139	−0.0659	−0.3111*
	(1.04)	(−0.86)	(−0.29)	(−1.76)
Size	0.0015	−0.0003	0.0017	−0.0005
	(0.64)	(−0.20)	(0.71)	(−0.29)
BM	0.0085	0.0131***	0.0085	0.0129***
	(1.26)	(2.83)	(1.28)	(2.80)
MOM	0.0037	0.0026	0.0028	0.0027
	(0.31)	(0.36)	(0.23)	(0.37)
AG	−0.0035	−0.0056**	−0.0035	−0.0055**
	(−1.17)	(−2.14)	(−1.18)	(−2.16)
GP	0.0231***	0.0329***	0.0228***	0.0322***
	(3.01)	(3.81)	(2.98)	(3.81)
Illiq	1937.90	−4383.9	2176.49	−3543.7
	(0.72)	(−0.83)	(0.87)	(−0.75)
No. Obs.	158,139	158,376	158,139	158,376
Adj. R^2	0.0379	0.0287	0.038	0.0289

Table 8: **Summary Statistics on Transition Programs.** This table reports the summary statistics on the transition programs. Panel A reports the distribution of program-level total transition volume (in $million), the number of distinct stocks traded in the program, and the total number of trades in the program. Panel B reports the distribution of program duration. The duration of a program is defined as the number of days between the first and last trades of the program. The column "Program %" reports the distribution by the number of programs. The column "Volume %" reports the distribution by the program-level trading volume.

Panel A: Program size and #trades					
	Mean	P25	P50	P75	Max
Volume ($mi)	248	27	92	238	8,702
# Stocks Traded	237	27	96	270	3,161
# Trades	578	47	173	516	52,316
Panel B: Program duration					
Days	Program%	Cumulative%		Volume%	Cumulative%
1	31.45	31.45		11.05	11.05
2	12.81	44.26		8.00	19.05
3-5	15.89	60.16		15.13	34.18
6-10	17.52	77.67		22.58	56.76
11-20	7.72	85.39		11.92	68.68
21-30	2.97	88.36		8.05	76.73
30+	11.64	100.00		23.27	100.00

Table 9: **Transition Trade Costs.** This table reports the Fama-MacBeth regression results. The unit of observation is at the transition trade level. The sample period is 2013-2024. The dependent variable is the trade cost (equation 9). We use the previous close price as the benchmark price for the calculation of trade cost in columns (1)-(3), and we use the current-day open price as the benchmark price in columns (4)-(6). The key dependent variable is trade size, defined as the trade dollar volume scaled by the stock dollar trading volume reported in CRSP on the same date. The controls are stock and program characteristics, including the natural logarithm of market capitalization, idiosyncratic volatility, Amihud illiquidity, daily turnover ratio, the inverse of stock price, NASDAQ-listed indicator, and the program's total dollar trading volume. We report the regression results in the sample of all trades, buy trades, and sell trades, separately. To estimate the coefficients, we first pool all trades in the same calendar month and run cross-sectional regressions. We then calculate the time-series average of the coefficient estimates and the associated t-statistics across months. t-statistics in parentheses are calculated based on standard errors with Newey-West correction of four lags. *, **, *** indicate significance at the 10%, 5%, and 1% level, respectively.

Benchmark Price:	Previous Close			Current Open		
Trade Type:	All	Buy	Sell	All	Buy	Sell
	(1)	(2)	(3)	(4)	(5)	(6)
TradeSize	0.010	0.049	0.035	0.012	0.051	0.005
	(1.28)	(0.87)	(1.59)	(1.12)	(1.04)	(1.11)
Size	-0.000***	-0.000***	-0.000	-0.000***	-0.000***	-0.000**
	(-3.37)	(-3.29)	(-1.35)	(-6.31)	(-4.42)	(-2.56)
IVol	0.026***	-0.025	0.035***	0.030***	-0.018**	0.045***
	(4.29)	(-1.41)	(5.78)	(4.17)	(-2.02)	(7.11)
illiq	51012.7**	-146916	50268.4*	33281.6**	21336.6	108115*
	(2.24)	(-0.79)	(1.96)	(2.52)	(0.08)	(1.67)
Turnover	-0.017**	0.004	-0.008	-0.012	-0.004	-0.003
	(-2.17)	(0.22)	(-0.68)	(-1.29)	(-0.21)	(-0.35)
PRC_inverse	0.002	0.002	0.014	0.002	-0.000	0.012
	(0.92)	(0.44)	(1.23)	(1.00)	(-0.09)	(1.54)
Nasdaq	0.000	0.000	-0.000	0.000	0.000	0.000
	(0.38)	(0.42)	(-0.17)	(1.63)	(0.16)	(1.43)
Program_volume	0.000	0.000	0.000	0.000**	0.000	0.000
	(1.21)	(0.17)	(0.93)	(2.35)	(0.58)	(1.09)
No. Obs.	872,353	390,980	481,373	872,334	390,977	481,357
Adj. R^2	0.024	0.04	0.043	0.028	0.036	0.046

Table 10: **Program-level Trade Cost.** This table reports the transition program-level trade cost (%). We first compute trade-level trade costs using equation (9), where we use either the previous close price or the current open price as the benchmark. We then compute the program-level trade cost as the volume-weighted or equal-weighted average of trade costs across all trades in the program. Finally, we sort all programs into quintiles by total program volume and report the average program-level trade cost for each quintile.

		Programs Quintiles by Total Volume				
Benchmark	Weight Scheme	1 (Small)	2	3	4	5 (Large)
Previous Close	Volume-weight	0.11	0.04	0.09	0.04	0.06
Previous Close	Equal-weight	0.11	0.06	0.09	0.06	0.09
Current Open	Volume-weight	0.15	0.08	0.09	0.07	0.09
Current Open	Equal-weight	0.16	0.09	0.08	0.08	0.10

Table 11: **The Usage of Transition Programs.** Panel A reports the time-series relationship between the occurrence of separate account (or mutual fund) fire sales and the occurrence of transition programs during 2013Q3-2021.Q4. We use the full-sample 10th percentile value of quarterly flows to define the fire sales for separate accounts or mutual funds in each quarter. SA_FireSale% (MF_FireSale%) is the number of separate account (mutual fund) fire sales in a quarter as a fraction of the number of existing separate accounts (mutual funds) in the quarter. Transit_Program% is the number of sales-oriented transition programs as a fraction of the number of existing separate accounts in the quarter. A program is defined as sales-oriented if the sales volume accounts for more than 50% of the total trading volume of the program. We perform a time-series regression of Transit_Program% on contemporaneous SA_FireSale% and MF_FireSale%, controlling for contemporaneous stock market liquidity, stock market return, and the lagged Transit_Program%. Standard errors are with Newey-West adjustment of one lag. In Panel B, we match transition programs with separate account-quarter observations in our sample (see Appendix Section C). We define a fund-quarter as experiencing extreme outflows if the flow is lower than the 10th or 5th percentile values of flows in the quarter. We report the probability of experiencing extreme outflows among the matched separate account-quarters and the full sample. We also report the p-value from testing the equality of the probabilities of extreme outflows between the matched and full samples.

Panel A: Time-series regressions

	(1)	(2)	(3)
SA_FireSale%	0.045*		0.077**
	(1.93)		(2.02)
MF_FireSale%		0.023	−0.028
		(1.00)	(−0.95)
Mkt_Liquidity	0.033	0.030	0.033
	(1.29)	(1.19)	(1.26)
Mkt_Ret	−0.007	−0.003	−0.009
	(−0.78)	(−0.30)	(−0.90)
Sentiment	−0.001	−0.001	−0.001*
	(−1.67)	(−1.57)	(−1.75)
Lag Transit_Program%	0.801***	0.781***	0.761***
	(2.96)	(2.67)	(2.64)
Intercept	0.000	0.003	0.000
	(0.14)	(0.78)	(0.12)
No. Obs.	34	34	34
Adj. R^2	0.328	0.291	0.314

Panel B: Fire-sale probability among matched sample

	(1)	(2)	(3)
	Pr(Bot 10% Flow)	Pr(Bot 10% Flow)	Median Flow
Matched SA-Quarter	34.34%	22.22%	−5.73%
All SA-Quarter	10%	5%	−0.39%
p-value of testing equality:	<0.0001	<0.0001	<0.0001

Appendix

A Additional Results

In this section, we present supporting evidence and additional robustness results that complement our main findings.

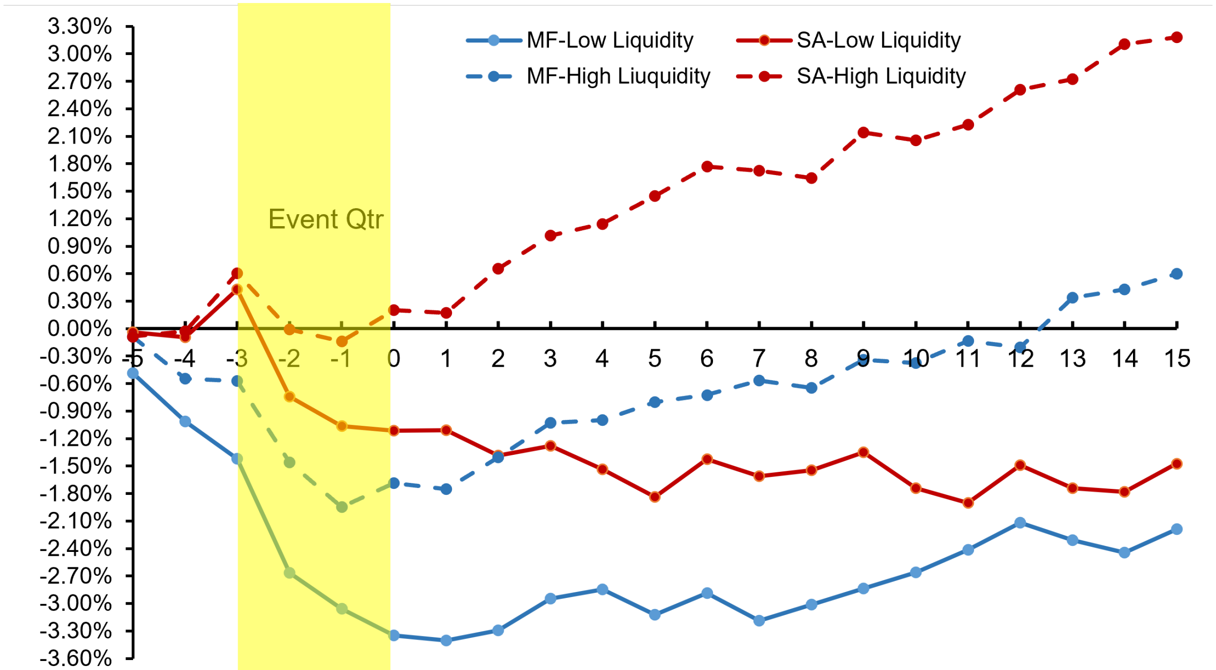


Figure A.1: **Fire-sale event CAR: Low versus high mariet liquidity.** This figure plots the event-time cumulative abnormal returns (CAR) associated with mutual fund fire sale and separate account fire sale events. The sample period of 2001.Q4-2024.Q4 is split into two halves based on mariet liquidity. We plot the fire-sale event CAR in low and high mariet liquidity periods separately.

Table A.1: **Fire-Sale Event CAR: Twin Fund Sample.** This table reports the event-time cumulative abnormal returns (CAR) associated with mutual fund fire sale and separate account fire sale events during 2001.Q4-2024.Q4. The test specifications follow Table 4, but we only use mutual funds or separate accounts with twin vehicles in this Table.

	Mutual Funds		Separate Accounts	
Event Month	CAR	*t*-value	CAR	*t*-value
-5	-0.21%	-1.27	0.05%	0.24
-4	-0.64%	-2.92	-0.07%	-0.26
-3	-0.75%	-2.94	0.11%	0.32
-2	-1.74%	-6.73	-0.40%	-1.01
-1	-2.07%	-6.64	-0.48%	-1.08
0	-2.12%	-5.77	-0.51%	-0.98
1	-2.26%	-5.95	-0.48%	-0.87
2	-1.89%	-5.20	-0.21%	-0.33
3	-1.86%	-4.43	0.03%	0.04
4	-1.85%	-4.18	0.08%	0.11
5	-1.68%	-3.64	0.15%	0.20
6	-1.39%	-2.92	0.51%	0.63
7	-1.28%	-2.43	0.71%	0.85
8	-1.08%	-1.96	0.91%	1.07
9	-0.87%	-1.55	0.97%	1.07
10	-0.68%	-1.14	0.89%	0.95
11	-0.48%	-0.82	0.89%	1.03
12	-0.41%	-0.65	1.34%	1.53
13	0.03%	0.04	1.20%	1.36
14	0.13%	0.17	1.29%	1.45
15	0.19%	0.24	1.37%	1.48

Table A.2: **Predict Stock Volatility by Fragility: Subsample by Mariet Liquidity.** This table reports the Fama-MacBeth regressions of predicting stock volatility by fragility in the subsamples classified by market liquidity. We split the sample period into two even halves based on the market liquidity measure of Pástor and Stambaugh (2003). Within each period, we re-perform the regression as in Table 5. *, **, *** indicate significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Market Liquidity:		Low			High	
$\sqrt{G}^{MF}$	0.194***		0.187***	0.195***		0.188***
	(5.463)		(4.926)	(5.347)		(4.708)
$\sqrt{G}^{SA}$		0.029***	0.013		0.021***	0.004
		(3.170)	(1.245)		(3.436)	(0.496)
Vol_Lag	0.764***	0.773***	0.763***	0.685***	0.697***	0.684***
	(23.225)	(23.811)	(23.121)	(39.506)	(42.184)	(39.582)
No. Obs	42,370	42,370	42,370	42,587	42,587	42,587
Adj. R^2	0.519	0.515	0.52	0.498	0.493	0.499

B Derivation of Fragility

In this section, we describe how we derive and estimate fragility. As in Greenwood and Thesmar (2011) (GT), we assume the following contemporaneous relationship between fund flow-induced trading and return of stock j:

$$r_{j,t} = \alpha + \lambda \frac{\sum_i \text{Shares}_{i,j,t-1} \text{Flow}_{i,t} \text{PSF}}{\text{Shrout}_{j,t-1}} + \varepsilon_{j,t}. \tag{11}$$

Here, $r_{j,t}$ is the return of stock j in quarter t, $\text{Shares}_{i,j,t-1}$ is the number of shares of stocks j held by fund i at the end of quarter $t-1$, $\text{Flow}_{\text{i,t}}$ is the percentage flow of fund i in quarter t, PSF is the partial scaling factor, and $\text{Shrout}_{j,t-1}$ is shares outstanding of stock j at the end of quarter $t-1$. The fraction, $\frac{\sum_i \text{Shares}_{i,j,t-1} \text{Flow}_{i,t} \text{PSF}}{\text{Shrout}_{j,t-1}}$, is effectively the FIT2 measure as in equation 4. λ is the price impact factor. The residual term, $\varepsilon_{j,t}$, has a conditional mean of zero and may capture other sources of variation of returns (e.g., news about fundamentals). The specification here is similar to the regression model we estimated as in equation 5.

Substituting fund ownership of stock j ($w_{i,j,t-1} = \frac{\text{Shares}_{\text{i,j,t-1}}}{Shrout_{j,t-1}}$) into equaiton 11, we get

$$r_{j,t} = \alpha + \lambda \sum_i w_{i,j,t-1} \text{Flow}_{i,t} \text{PSF} + \varepsilon_{j,t}. \tag{12}$$

Taking variance on both sides, we obtain the conditional variance of stock j at the end of quarter t as:

$$\text{Var}_t(r_{j,t+1}) = \lambda^2 {W_{j,t}}' E_t(\Omega_{t+1}) W_{j,t} + \text{Var}_t\left(\varepsilon_{j,t+1}\right) \tag{13}$$

Here, $E_t(\Omega_{t+1})$ is the conditional variance-covariance matrix of fund flows in quarter $t+1$ and $W'_{j,t} = [w_{1,j,t}, w_{2,j,t}, ..., w_{K,j,t}]$ is the vector of mutual fund ownership of stock j.

Similar to GT, we define the fragility of stock j in quarter t as

$$G_{j,t} = {W_{j,t}}' E_t(\Omega_{t+1}) W_{j,t}. \tag{14}$$

To estimate $E_t(\Omega_{t+1})$, we calculate the variance-covariance matrix of mutual fund flows using observations in the most recent eight quarters (including quarter t), and we require a fund do not have missing quarterly flows in the eight-quarter rolling window. The summary statistics of fragility and co-fragility are reported in Table 1.

C Transition Management Program Matching

In this section, we outline our methodology for linking transition management programs to separate accounts.

First, we restrict the sample to programs satisfying two constraints: (1) the execution occurs within a single calendar month, and (2) the portfolio comprises at least 10 unique common stocks. Share quantities are normalized using CRSP cumulative adjustment factors to ensure comparability between execution and reporting dates.

Second, we classify programs based on the *buy-sell ratio*, defined as the net change in principal divided by the total principal (Net Flow/Principal). Programs with an absolute ratio exceeding 0.90 are labeled *uni-directional*; otherwise, they are *bi-directional*. This distinction addresses the identification challenge specific to bi-directional reallocations: *in-kind transfers*, where overlapping positions between legacy and target portfolios are retained without generating trade records.

For *uni-directional* programs, we match net-sell programs against the Separate Account's previous-period holdings (within 180 days prior) and net-buy programs against subsequent-period holdings (within 180 days post). A candidate pair is confirmed as a match if it meets four criteria: (1) matched securities represent at least 80% of the program's total principal; (2) the Pearson correlation and cosine similarity between adjusted trade weights and holding weights exceed 0.90 for both the full portfolio and the core subset (securities with weights $> 1\%$); (3) the fund's quarterly net flow to transition principal ratio falls within $[0.5, 2.0]$; and (4) at least 10 unique securities are matched.

For *bi-directional* programs, identification is complicated by overlapping positions absent from trade records. We implement a two-step procedure to address this. First, we apply a **pre-screening filter**: a candidate fund must hold at least 8 of the program's top 10 securities (ranked by trading volume) and report a quarterly net flow between 1× and 5× the transition's directional trading volume. Second, we model the matching as a robust regression problem using the Random Sample Consensus (RANSAC) algorithm. Unlike standard Ordinary Least Squares (OLS), RANSAC iteratively estimates parameters from random subsets of inliers, making it resilient to outliers—specifically, stationary holdings that generate no trade records. The model is specified as:

$$\Delta\text{Trade}_{i,p} = \beta_{sell} H_{i,f_{sell}} + \beta_{buy} H_{i,f_{buy}} + \epsilon_i \tag{15}$$

where $\Delta\text{Trade}_{i,p}$ represents the net change of security i in program p, $H_{i,f_{sell}}$ and $H_{i,f_{buy}}$ denote the holdings in the candidate sell and buy funds, and ϵ_i is the error term.

To prevent spurious fitting to zero-trade noise, we employ a weighted estimation scheme where securities with non-zero trading volume are assigned a relative importance weight of 100. We estimate this model using both share-based and value-based inputs. A match is validated if either specification meets the following criteria: (1) the weighted RANSAC regression yields an $R^2 > 70\%$; (2) the identified inlier securities explain more than 40% of the total transition trading volume; and (3) the regression coefficients are economically consistent ($\beta_{sell} < 0$ and $\beta_{buy} > 0$).