Peer fragility, liquidity preferences, and the propagation of financial shocks*

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Abstract

This paper provides empirical evidence of mutual fund fragility spillovers through common asset ownership. Using data on U.S. active equity mutual funds, we measure peer fragility based on two factors: strategic complementarities in peers' redemptions, inferred from investor composition, and a fund's exposure to the *expected* fire-sale pressure of other funds. We find that funds facing higher peer fragility actively increase portfolio liquidity during market stress. This adjustment is not driven by investor outflows, which do not respond to peer fragility. Instead, fund managers appear to act preemptively in anticipation of liquidity needs. The resulting increase in demand for liquidity imposes negative externalities and transitory price pressure, amplifying systemic risk. To address identification concerns, we exploit variation from three natural experiments: unexpected volatility shocks, the 2003 mutual fund late trading scandal, and the collapse of Lehman Brothers.

Keywords: Peer fragility, strategic complementarities, financial fragility, mutual fund redemptions, liquidity preferences, market stress, crises spillover effects

JEL classification: G01, G11, G14, G20, G23

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1 Introduction

There is a growing interest among academics and policymakers in financial fragility arising from the liquidity transformation activities of institutional investors. In particular, the pricing mechanism used by open-end mutual funds may generate a first-mover advantage among their investors, which can amplify the effects of negative shocks—especially during periods of market-wide stress when liquidity is scarce and strategic complementarities are significant (see e.g., Chen, Goldstein, and Jiang, 2010; Zeng, 2018). The general consensus is that the asset illiquidity of mutual funds renders them vulnerable to investor runs, which may create fragility in the mutual fund sector. The first-mover advantage incentivizes investors to redeem their shares preemptively if they expect others to do the same.

Another strand of literature emphasizes that capital flows can induce widespread trading in individual securities, generating institutional price pressure that affects fund performance. This, in turn, can influence not only the capital flows of the affected fund but also those of other funds holding the same assets (e.g., Falato, Hortaçsu, Li, and Shin, 2021).

In this paper, we examine how fragility in one mutual fund can spill over to others—a phenomenon we term peer fragility. This constitutes an additional channel through which negative shocks can be amplified, particularly during periods of market stress. Fragility among peer funds threatens a given fund's portfolio by raising the risk of correlated asset sales, thereby influencing fund managers' portfolio decisions.

Following Rzeźnik (2025), we begin by documenting that mutual funds actively manage their portfolio liquidity in response to fragility risks. Specifically, we find that proxies for strategic complementarities—used to capture fund fragility—predict shifts toward more liquid asset holdings during episodes of market-wide stress.[1] We then create a novel peer fragility index to capture the potential threat that peer fund redemptions pose to a fund's portfolio performance and liquidity through common ownership of assets. The index combines two key dimensions: (1) the degree of strategic complementarities in peer redemptions, based on the investor composition of peer funds; and (2) a fund's exposure

[1] Rzeźnik (2025) documents that equity mutual funds shift toward more liquid assets during market stress, particularly when exposed to strategic complementarities among investors. The paper shows that mutual fund liquidity management follows a liquidation pecking order based on relative stock illiquidity, with stronger responses among more fragile funds. This response not only preserves redemption flexibility but also contributes to movements in the market-wide liquidity premium, highlighting the broader pricing implications of liquidity management. See also Ben-Rephael (2017), Huang (2020), and Jiang, Li, and Wang (2021).

to the *expected* fire-sale pressure generated by peers. We show that, much like a fund's own fragility, funds with greater peer fragility increase portfolio liquidity during market stress. While fund managers likely take peer fragility into account as part of their regular portfolio management, its influence becomes especially pronounced during market-wide stress, when peer withdrawals can directly affect a fund's portfolio decisions and indirectly affect the performance and liquidity of other funds via common asset holdings.

Although mutual funds respond similarly to both types of fragility–by increasing liquidity–the underlying mechanisms driving these responses are fundamentally different. A fund's own fragility manifests directly through strategic complementarities in redemption behavior among its investors (Chen et al., 2010; Goldstein, Jiang, and Ng, 2017). In contrast, peer fragility operates indirectly, through common asset holdings and anticipated fire-sale spillovers, which can impose negative externalities on portfolio performance and liquidity even in the absence of actual flow pressure.

We motivate our main findings in Figure 1, which documents the relationship between market volatility and the difference in flows and liquidity preferences between high- and low-fragility funds. Panel A focuses on funds' exposure to own fragility (hereafter, CGJ fragility). As volatility rises, high-CGJ fragility funds experience greater outflows (red triangles) and increase the demand for portfolio liquidity (blue circles) relative to their less fragile peers.[2] Panel B shows that peer-fragile funds similarly shift toward more liquid holdings as volatility increases. However, unlike CGJ fragility, peer fragility does not correspond to differential investor flows.

The main premise of our paper is that mutual funds are subject to at least two sources of financial fragility: strategic complementarities among investors and potential spill-overs from peers. Regardless of the fragility's origin—whether stemming from a first-mover advantage among a fund's own investors or from vulnerabilities transmitted through peers—fund managers actively shift toward more liquid portfolios to mitigate the adverse effects. Increasing liquidity helps minimize the costs associated with potential forced sales and thereby reduces the incentive for early redemptions.

To illustrate the mechanism, consider two funds with similar portfolios but very different peer groups. The peers of the first fund are primarily held by small retail investors, whereas the peers of the second fund are dominated by large institutional investors. During periods of market stress, the first-mover advantage in redemption is more likely to

[2]We measure liquidity preferences using an index of active liquidity management (ALMGMT), which captures changes in a fund's average portfolio illiquidity due to shifts in composition. A more negative value of the index reflects a move toward more liquid holdings.

emerge among retail investors, who are more sensitive to the behavior of others (Goldstein et al., 2017). This can trigger withdrawals from the peers of the first fund, leading to forced asset sales and, in turn, affecting the prices and liquidity of commonly held securities. In contrast, institutional investors tend to be less reactive to the behavior of others and are less likely to redeem en masse, making the second fund less vulnerable to peer-induced fragility.

As a result, the first fund faces a dual threat: it is exposed both to strategic complementarities among its own investors and to fragility arising from peer behavior. This heightened vulnerability increases the fund's demand for liquidity. Importantly, because peer fragility operates indirectly—through common asset holdings rather than direct redemptions—we do not expect it to have a noticeable effect on the fund's own investor flows. Using data on net flows and portfolio holdings of U.S. mutual funds investing in domestic equities between January 2002 and June 2020, we find strong empirical support for these hypotheses.

We begin our analysis by measuring fund's exposure to strategic complementarities among investors. Following the empirical evidence in Chen et al. (2010) and Goldstein et al. (2017), we identify two key drivers of the first-mover advantage in redemption decisions: the illiquidity of the fund's portfolio and the composition of its investor base. Building on Rzeźnik (2025), we construct a fund-specific fragility index that captures multiple dimensions of fragility and allows for interaction effects between portfolio illiquidity and investor type. We then relate these fragility measures to mutual fund liquidity preferences and investor flows during periods of market stress–when market liquidity declines and strategic complementarities are particularly salient. We estimate that CGJ-fragile funds increase portfolio liquidity by 0.11 standard deviations during high-volatility periods relative to non-fragile funds.[3]

Next, we examine how mutual fund managers respond to the exposure to peer fragility. We use two proxies for the fragility of fund's peers: the investor composition of peers and potential price and liquidity pressure due to *expected* fire sales of other funds. The two measures allow us to capture a fund's exposure to potential negative externalities induced by other funds and their investors. We find that funds react in a similar manner

[3]These findings suggest that fund managers proactively shift toward more liquid asset allocations to manage the risks associated with strategic complementarities. Absent mechanisms such as swing pricing, which reduce first-mover incentives by adjusting redemption values to reflect liquidity costs (Jin, Kacperczyk, Kahraman, and Suntheim, 2022), mutual funds often rely on preemptive liquidity management to mitigate redemption-driven fire-sale risk. Rzeźnik (2025) documents that fragility-prone funds follow a liquidation pecking order, reducing exposure to relatively illiquid assets during times of stress.

to peer fragility as to their own fragility by rebalancing their portfolios toward more liquid assets. In times of market stress, peer-fragile funds actively increase the liquidity of their portfolios by 0.21 standard deviations compared to funds with a lower degree of peer fragility. In contrast to the CGJ fragility results, we find no significant differences in investor flows between funds with high and low exposure to peer fragility. This result provides evidence of a new channel through which peer fragility can affect the portfolio allocation decisions of fund managers.

In our main analysis, we measure mutual fund liquidity preferences by decomposing the change in a fund's portfolio liquidity between two months via a shift-share analysis and isolating shifts due to active modification of a portfolio's composition in terms of holdings, which is directly under the managers' control (Rzeźnik, 2025). To better understand the way in which funds increase liquidity of their portfolio, we also examine mutual fund net-trading of securities in different liquidity bins. Consistent with Brown, Carlin, and Lobo (2010), we document that CGJ fragile funds enhance the portfolio's liquidity by net-selling the most illiquid holdings. On the other hand, peer fragile funds increase the liquidity of their portfolio by net-purchasing more liquid stocks. The intuition is that peer fragile funds do not experience investor withdrawals; thus, they can avoid costly sales and increase portfolio liquidity by holding more liquid stocks.

Our analysis uses the VIX as a proxy for periods of market stress. Since market volatility is persistent and likely correlated with unobservable changes in fund's investment opportunity set, it might be the case that mutual funds adjust the composition of their portfolios in terms of liquidity in response to changing investment opportunities or in anticipation of market uncertainty. In order to address this potential issue, we use three main empirical strategies. First, we investigate mutual fund liquidity preferences around sudden *jumps* in VIX, which we call 'volatility shocks.' We document that liquidity preferences of fragile and less fragile funds are indistinguishable from each other before the volatility shock occurs. However, CGJ and peer fragile funds rebalance their portfolio more aggressively toward liquid stocks in the first and the second month since the unexpected volatility jump. Thus, exploiting volatility jumps allows us to address a potential concern that other factors (e.g., previous shifts in volatility or market performance) explain our findings and also allows us to examine the dynamics of portfolio adjustment. Consistent with our prior results, redemption obligations significantly increase for funds with greater exposure to strategic complementarities among investors once the volatility shock takes place. However, peer-fragile funds are subject to the same investor flows as less peer-fragile funds during unexpected volatility shock periods.

Second, we exploit the 2003 mutual fund late trading scandal, which took place during a period of relative market calmness and resulted in unexpected outflows from scandal-implicated funds (McCabe, 2008; Kisin, 2011; Antón and Polk, 2014). We focus on *non-scandal* funds and their exposure to peer fragility due to the scandal. To capture the peer fragility, we compute stock-level imputed outflows from scandal-involved funds and aggregate them into a portfolio-level measure. We show that before the scandal outbreak, funds more exposed to peer fragility (i.e., with greater imputed outflows) did not differ in their liquidity preferences. However, after September 2003 (the initial month of scandal outbreak) non-scandal funds with greater exposure to withdrawals from scandal-implicated funds, through common stock ownership, significantly and actively rebalance their portfolio toward more liquid stocks. Consistent with our previous results, we do not observe any flow responses of non-scandal funds to scandal-induced peer fragility. This evidence suggests that our baseline results are not confounded by stress-driven unobservable changes to funds' investment opportunity set, but directly to the exposure to scandal-driven withdrawals from their peers. This highlights that fragility contagion spills over from a set of distressed funds to their peers based on portfolio linkages and affects liquidity demands.

Third, we focus on the 2008 financial crisis and examine heterogeneity in mutual funds' and their peers' exposure to the Great Recession. We measure a fund's vulnerability by calculating the share of its portfolio invested in financial sector stocks (Hau and Lai, 2017). To avoid redundancy in defining peer groups, we base peer relationships on non-financial holdings. We find that investor flows do not respond to peers' exposure to the financial crisis. However, fund managers actively rebalance their portfolios toward more liquid assets following the collapse of Lehman Brothers—even after controlling for the fund's own exposure to the crisis. This suggests that peer fragility, as revealed during the crisis, influenced portfolio decisions through perceived spillover risks, independent of a fund's direct exposure.

Given recent evidence that mutual funds can propagate financial crises (Manconi, Massa, and Yasuda, 2012; Hau and Lai, 2017) and exert price pressure through their demand for liquidity during periods of market stress (Vayanos, 2004; Ben-Rephael, 2017; Rzeźnik, 2025), we investigate whether the heightened liquidity preferences of funds exposed to peer fragility have measurable effects on stock prices. Specifically, we examine heterogeneity in stocks' exposure to peer fragility around the onset of the 2008 financial crisis.

In the four quarters leading up to the collapse of Lehman Brothers, we find no significant relationship between abnormal returns (as measured by Carhart, 1997) and either own or peer exposure to the crisis. However, following Lehman's bankruptcy in September 2008, we observe a temporary underperformance of non-financial stocks held by funds with high exposure to financial sector assets – both directly and through their peers. Specifically, non-financial stocks held by funds with high own exposure underperform by 7.04 and 7.50 basis points in the third and fourth quarters of 2008, respectively. The underperformance is even more pronounced for non-financial stocks held by funds with peers highly exposed to the crisis, which decline by 12.07 and 8.06 basis points over the same period. Importantly, the negative price impact of peer exposure remains significant even after controlling for CGJ fragility, market capitalization, mutual fund ownership, and industry fixed effects. These findings highlight the independent role of peer fragility in driving price pressure and underscore its importance as a mechanism for stock market 'contagion."

Related Literature. This paper is related to, and builds on, three distinct lines of literature.

First, our paper contributes to a growing literature that focuses on the presence of strategic complementarities among investors and their contribution to fragility in financial markets. In the seminal work of Chen et al. (2010), the authors show that the threat of potential outflows can create a first-mover advantage, where non-redeeming investors bear the costs of redeeming investors' actions. The incentive to withdraw increases with portfolio illiquidity and with market stress. Similarly, Goldstein et al. (2017) document that strategic complementarities among mutual fund investors strengthen when market illiquidity is high, resulting in greater sensitivity of outflows to poor performance during stress episodes. Massa, Schumacher, and Wang (2021) show that mutual funds strategically reduce holdings in stocks with increasingly concentrated ownership, anticipating the potential fragility such changes create. Rzeźnik (2025) complements this line of work by documenting that mutual funds facing redemption pressure respond to volatility-induced stress by rebalancing away from illiquid holdings, especially when exposed to investor complementarities. Our paper extends these insights by showing that mutual funds also behave strategically in response to fragility among their peers. By increasing portfolio liquidity, funds mitigate the negative externalities that peer fragility imposes through common ownership. Our results are also complementary to Falato et al. (2021) and Chernenko and Sunderam (2020), who show that fire sales affect portfolio composition. Our contribution to this literature is to provide, to our knowledge, the first empirical evidence that mutual funds respond to potential spillovers from peers—even in the absence of direct changes in their own investor flows.

Second, our paper contributes to the literature examining mutual fund liquidity preferences in times of market-wide stress or uncertainty. According to Vayanos's (2004) model, periods of heightened market uncertainty coincide with deteriorating mutual fund performance and redemption pressure, prompting managers to prioritize flexibility by shifting toward liquid assets. Several recent papers provide empirical support for this mechanism, including Ben-Rephael (2017), Jiang et al. (2021), Huang (2020), and Rzeźnik (2025), who shows that mutual funds reallocate toward more liquid stocks in response to market volatility, especially when fragility risk is high and liquidation constraints bind. We build on this literature by documenting two distinct channels driving liquidity demand under stress: mutual funds respond not only to strategic complementarities among their own investors, but also to fragility that arises from common asset holdings with other vulnerable funds. These two sources of fragility jointly shape funds' liquidity management during times of market-wide stress.[4]

Third, our paper contributes to a small but growing literature on commonalities and interdependencies across fund portfolios. Blocher (2016) documents a positive feedback loop among mutual funds: managers respond to outflows by selling assets, which depresses prices and triggers further redemptions by return-sensitive investors. Other funds holding the same securities are thus indirectly affected, perpetuating the cycle. Relatedly, Dyakova and Verbeek (2013) and Shive and Yun (2013) show that hedge funds and other investors may front-run anticipated fire sales. Nanda and Wei (2018) argue that mutual fund managers internalize network externalities by adjusting portfolio overlap when flow correlations increase. Building on these insights, we show that mutual funds are indirectly exposed to peer fragility through co-ownership of common assets. In response, they increase portfolio liquidity during stress episodes, thereby managing their exposure to potential peer-driven fire sales.

The paper is organized as follows. The next section presents hypothesis development. In section 3, we describe the data and the variable construction. Section 4 discusses our empirical strategy and baseline results. In Section 5, we explore three quasi-natural experiments and show the robustness of our results. Section 6concludes.

[4]See also Jin et al. (2022), who shows that swing pricing can mitigate redemption-driven fragility by reducing first-mover incentives. In the absence of such mechanisms, Rzeźnik (2025) finds that mutual funds proactively manage portfolio liquidity to limit the impact of redemptions, consistent with our finding that peer fragility triggers similar preemptive behavior.

2 Hypothesis Development

Our main hypotheses are based on the simple premise that outside factors affect mutual fund portfolio allocation decisions. When faced with heightened market uncertainty (e.g., Ben-Rephael, 2017; Huang, 2020), strategic complementarities among investors (Chen et al., 2010; Goldstein et al., 2017; Rzeźnik, 2025), shifts in expected stock ownership concentration (Massa et al., 2021), or fire sales by other funds (Falato et al., 2021), fund managers tend to adjust their portfolio composition to mitigate potential adverse effects. Similarly, rising fragility among mutual fund peers can threaten fund performance and portfolio liquidity. In response, managers increase their holdings of liquid assets to buffer against these risks. This gives rise to our first hypothesis.

Hypothesis 1: Mutual funds with more fragile peers actively increase the liquidity of their portfolios during periods of market stress.

Intuitively, both amplified withdrawals from peer funds and fire sales of commonly held assets can impose negative externalities on a focal fund. Peers with higher retail ownership–where strategic complementarities are more pronounced–are more likely to experience redemptions during periods of market stress. As a result, funds surrounded by retail-oriented peers face heightened fragility. Similarly, funds holding assets that are likely to come under price pressure due to fire sales by peer funds are also more exposed to financial fragility.

We combine both peer fragility proxies into a single peer index and relate mutual fund liquidity preferences to fund's peer fragility exposure during episodes of market stress in a panel regression with fund and time fixed effects, while controlling for fund's CGJ fragility. To ensure the robustness of our results, we also explore three quasi-natural experiments: sudden and sizeable market volatility jumps, the 2003 mutual fund trading scandal, and the Great Recession.

Peer fragility poses a potential threat to fund performance and portfolio liquidity, even if the risk has not yet materialized. While strategic complementarities amplify investor withdrawals in response to poor past performance (Chen et al., 2010; Goldstein et al., 2017), peer fragility is less visible to the average investor and therefore unlikely to trigger a first-mover advantage in redemption decisions. This distinction leads to our second hypothesis.

Hypothesis 2: In contrast to CGJ fragility, peer fragility does not directly affect mutual fund net flows.

Motivated by Manconi et al. (2012) and Hau and Lai (2017), who study the propagation of financial crises by distressed funds during the Great Recession, we examine the link between increased demand for liquidity by mutual funds subject to peer fragility and stock prices. If non-financial stocks held by CGJ fragile funds experienced a negative price pressure during the 2008 financial crisis, then the peer fragility-induced demand for liquidity may transiently affect the stock prices as well. A non-financial stock held by a fund experiencing intensified withdrawals is more likely to be sold not only by the fund itself but also by other funds that co-hold the stock. This, in turn, would be reflected in temporarily depressed stock prices. This leads to the third hypothesis.

Hypothesis 3: During periods of market stress, peer fragility-induced liquidity demand leads to temporary price pressure on commonly held non-financial stocks.

Our empirical analysis focuses on these three hypotheses to investigate the underlying mechanism of peer fragility, its role in mutual fund portfolio allocation decisions, and asset pricing consequences. We now describe the data and empirical methodology.

3 Data and Variable Construction

3.1 Data Description

This section describes our data sources, outlines the procedures used to process the data, and explains the construction of the key variables used in the analysis. We also present summary statistics to characterize the sample.

3.2 Mutual fund and stock data

We use monthly mutual fund holdings data from Morningstar covering the period January 2002 to May 2020. This dataset is compiled from both mandatory SEC filings and voluntary disclosures. Our sample focuses on domestic mutual funds that actively invest in U.S. equities. Additional fund-level information—including total net assets (TNA), net returns, net flows, cash holdings, and other characteristics—is also obtained from Morningstar. For funds with multiple share classes, we compute TNA-weighted averages of net returns and cash holdings across all share classes to construct fund-level measures. Net flows are reported directly at the fund level. Our data processing procedures closely follow those in Rzeźnik (2025).

Stock-level data, including daily returns, prices, trading volumes, and shares outstanding for common stocks (share codes 10 and 11), are obtained from the Center for Research in Security Prices (CRSP). We use CUSIP identifiers to merge mutual fund holdings with CRSP stock data. To ensure consistency, we retain only those mutual funds for which at least 70% of the reported holdings (by value) are identified as common U.S. equities and successfully matched to CRSP. To measure market uncertainty, we use daily VIX observations from the Chicago Board Options Exchange (CBOE). Our final sample consists of 1,437 distinct funds and approximately 114,000 fund-month observations.

3.3 Active liquidity management measure and mutual fund flows

We use Amihud's (2002) measure to proxy for stock liquidity. For each stock s with at least 15 days of return and dollar volume data in a month t, we aggregate daily Amihud measures into a monthly average, $\text{Illiq}_{s,t}$. To reduce the influence of extreme observations, we choose a square-root transformation of the Amihud measure.[5] We use a stock-level liquidity measure to compute a monthly value-weighted illiquidity measure at the mutual fund level, $\text{Illiq}_{f,t}$, with weights equal to the percentage of a fund's portfolio invested in the stock.

Existing studies show that market volatility affects a stock's liquidity (e.g., Brunnermeier and Pedersen, 2009; Chung and Chuwonganant, 2014).[6] Furthermore, the liquidity of a fund's portfolio can change between two months for three reasons: its holdings become more or less liquid, the price of the holdings has changed, thus the weights are modified, and a fund manager actively manages the liquidity of the portfolio by trading securities. To separate these three effects, we follow Rzeźnik (2025) and perform a shift-share analysis by decomposing the change in the portfolio's liquidity into three

[5]Following Chordia, Huh, and Subrahmanyam (2009), Hasbrouck (2009), and Chen et al. (2010), among others, we use the square-root transformation of Amihud measure because it enables us to include cash holdings into the active liquidity management measure in a later stage of our analysis. Our results are robust to other Amihud measure transformations, such as log transformation.

[6]Chung and Chuwonganant (2014) shows that the liquidity of a single stock is strongly related both to its own risk and to the level of uncertainty in the market as a whole. In their theoretical model, Brunnermeier and Pedersen (2009) also predict that increases in VIX coincide with drops in the market liquidity, because market-makers' liquidity provision is limited when the market volatility is high.

components in the following way:

$$
\begin{aligned}
\Delta \text{Illiq}_{f,t} &= \sum_{s=1}^{\text{S}} \omega_{s,f,t} \cdot \text{Illiq}_{s,t} - \sum_{s=1}^{\text{S}} \omega_{s,f,t-1} \cdot \text{Illiq}_{s,t-1} \qquad (1)\\
&= \underbrace{\sum_{s=1}^{\text{S}} \omega_{s,f,t} \left(\text{Illiq}_{s,t} - \text{Illiq}_{s,t-1}\right) + \sum_{s=1}^{\text{S}} \text{Illiq}_{s,t-1} \left(\omega_{s,f,t} - \omega^{*}_{s,f,t}\right)}_{\text{Passive change in portfolio's liquidity}} \\
&\quad + \underbrace{\sum_{s=1}^{\text{S}} \text{Illiq}_{s,t-1} \left(\omega^{*}_{s,f,t} - \omega_{s,f,t-1}\right)}_{\text{Active liquidity management, ALMgmt}_{f,t}} \;,
\end{aligned}
$$

where $\omega^{*}_{s,f,t}$ is a weight of stock s in fund's portfolio f at time t given that the stock price remains unchanged since $t-1$. The first term denotes the change in a portfolio's liquidity due to a market-wide change in an individual stock's Amihud measure. The second component reflects how the shifts in holdings' prices affect the portfolio's liquidity. The last term is our measure of a fund's active liquidity management $\text{ALMgmt}_{f,t}$, which is obtained by isolating the component of the change in a portfolio's liquidity directly under the fund manager's control. It reflects the change in the composition of the holdings as a consequence of asset purchases and sales actively performed by the fund's manager. Since the Amihud measure increases with illiquidity, a positive (negative) value of a fund's active liquidity management measure indicates a portfolio's rebalancing toward less (more) liquid stocks.

3.4 CGJ fragility

Recent empirical studies by Chen et al. (2010) and Goldstein et al. (2017) document two crucial factors giving rise to strategic complementarities among investors: the illiquidity of a portfolio and the composition of mutual fund investors. The portfolio's illiquidity makes investor withdrawals more costly, which creates a first-mover advantage in the redemption decision. We use two measures to capture the degree of fund's illiquidity: a value-weighted Amihud measure of a portfolio, $\text{Illiq}_{f,t}$, and its illiquidity risk, $\beta^{\text{Illiq}}_{f,t}$. To construct the latter, we compute mutual fund return sensitivity to market-wide innovations in liquidity, $\beta^{\text{Illiq}}_{f,t-1}$. Mutual funds with high $\beta^{\text{Illiq}}_{f,t-1}$ hold stocks that experience significant price discounts in times of liquidity dry-ups, which could lead to underperformance and costly investor withdrawals. We compute $\beta^{\text{Illiq}}_{f,t}$ by using a 12-month rolling-window regression of daily fund net excess returns $r_{f,d}$ on market excess return, r_d^{Mkt}, and on lead, lag, and contemporaneous innovations in market illiquidity ($\eta_{d-1}^{\mathrm{Mkt}}$, η_d^{Mkt}, $\eta_{d+1}^{\mathrm{Mkt}}$). We follow Acharya and Pedersen (2005) to construct innovations in market illiquidity and estimate the following regression:

$$r_{f,d} = \beta_0 + \beta_{f,t}^{\mathrm{Mkt}} r_d^{\mathrm{Mkt}} + \beta_{f,t}^{\mathrm{Illiq}_{d-1}} \eta_{d-1}^{\mathrm{Mkt}} + \beta_{f,t}^{\mathrm{Illiq}_d} \eta_d^{\mathrm{Mkt}} + \beta_{f,t}^{\mathrm{Illiq}_{d+1}} \eta_{d+1}^{\mathrm{Mkt}} + \varepsilon_{f,d}. \tag{2}$$

The mutual fund return sensitivity to market-wide innovations in liquidity, $\beta_{f,t}^{\mathrm{Illiq}}$, is computed as a sum of $\beta_{f,t}^{\mathrm{Illiq}_{d-1}}$,$\beta_{f,t}^{\mathrm{Illiq}_d}$, and $\beta_{f,t}^{\mathrm{Illiq}_{d+1}}$. Next, we look at the composition of mutual fund investors. When mutual funds are held by a few large investors, the threat of costly outflows decreases, since the investors are more likely to internalize the costly withdrawals. We measure mutual fund exposure to strategic complementarities due to the shareholders' composition with a fraction of retail ownership of fund f in month t, $\mathrm{Retail}_{f,t}$. We define share classes A, B, C, D, S , and T with a minimum initial purchase requirement of less than $50,000 as retail share classes.

Finally, we construct a fragility index, which allows us to combine all three proxies for mutual fund exposure to strategic complementarities among investors. We use a similar approach to Asness, Frazzini, and Pedersen (2019) in their construction of the quality measure to compute the fragility index. We standardize $\mathrm{Illiq}_{f,t}$, $\beta_{f,t}^{\mathrm{LIQ}}$, and $\mathrm{Retail}_{f,t}$ to put each measure on equal footing and obtain z-scores. Our fragility index is the sum of the individual z-scores:

$$\text{Fragility Index}_{f,t} = z\left(z\mathrm{Illiq}_{f,t} + z\beta_{f,t}^{\mathrm{LIQ}} + z\mathrm{Retail}_{f,t}\right). \tag{3}$$

To ease the interpretation of our results we also standardize the sum of the individual z-scores.

3.5 Peer fragility

To quantify a mutual fund's exposure to the fragility of its peers, we examine how a liquidity shock to one fund can spill over to others. Two key factors drive this transmission. First, portfolio overlap plays a central role: In the absence of overlapping holdings across funds, the potential for contagion is minimal. Second, investor composition affects the strength of the first-mover advantage in redemptions. Funds held primarily by large, institutional investors tend to exhibit lower flow–performance sensitivity, while those with higher retail ownership are more fragile (Chen et al., 2010; Goldstein et al., 2017). We combine these two components to construct the first measure of peer fragility exposure:

$$\text{Peer Retail}_{f,t} = \sum_{s=1}^{S} \omega_{s,f,t} \text{Retail}_{s,t}^{-f}, \tag{4}$$

where $\text{Retail}_{s,t}^{-f}$ denotes the weighted average share of retail ownership among all other funds (excluding fund f) that hold stock s, and $\omega_{s,f,t}$ is the weight of stock s in fund f's portfolio.

The second proxy for a fund's vulnerability to its peers' fragility captures a fund's exposure to the potential fire sale of stocks held by the mutual fund. Specifically, we use a flow-to-stock measure proposed by Wardlaw (2020) that captures a potential fire sale pressure. We calculate it for each fund-stock pair in a given month:

$$\text{Peer FtS}_{i,f,t} = \sum_{j=1,\, j\neq f}^{\text{F}} |\text{Net-Flow}_{j,t}| \cdot \frac{\text{Shares}_{i,j,t-1}}{\text{Volume}_{i,t}}, \tag{5}$$

conditional on the outflow of fund j being greater than 2.5% of total net assets in month t. $\text{Shares}_{i,j,t-1}$ is the number of shares held by fund j of stock i at the end of month $t-1$. $\text{Volume}_{i,t}$ denotes share trading volume of stock i over month t. $|\text{Net-Flow}_{j,t}|$ is an absolute value of fund j net outflows over month t. F is a number of funds other than fund f. Peer $\text{FtS}_{i,f,t}$ captures potential fire sale pressure induced by withdrawals from all funds, but fund f. Thus, Peer $\text{FtS}_{i,f,t}$ is not contaminated by fund f's own 'fragility,' that is, investor redemptions from fund f. We aggregate the flow-to-stock measure to the fund level, by computing value-weighted average exposure to potential fire-sale price pressure – Peer $\text{FtS}_{f,t}$.

Similar to Fragility $\text{Index}_{f,t}$, we also construct a peer fragility index Peer $\text{Index}_{f,t}$. We construct it in the same way, by summing z-scored measures of Peer $\text{Retail}_{f,t}$ and Peer $\text{FtS}_{f,t}$. To ease the interpretation of our results, we also standardize Peer $\text{Index}_{f,t}$ to have a mean of zero and a standard deviation of one.

3.6 Other variables

We follow recent empirical studies (e.g., Rey, 2015; Goldstein et al., 2017; Jin et al., 2022) and use the Volatility Index (VIX) as a proxy for market stress. On top of controlling for fund and time fixed effects in our analysis, we also include four fund-specific, time-varying controls: the natural logarithm of total net assets, $\text{Log(TNA)}_{f,t-1}$, the fund's single-factor alpha, CAPM-Alpha$_{f,t-1}$, the net-expense ratio, Expense$_{f,t-1}$, and Nanda and Wei's (2018) overlap management measure, Mgmt Overlap$_{f,t-1}$.

3.7 Summary statistics

The reported summary statistics in Table 1 Panel A provide some general overview of mutual funds liquidity preferences. The mean (median) fund illiquidity is 1.970 (1.089), meaning that mutual funds invest in the top 12% of most liquid stocks.[7] They keep on average 2.5% of their holdings in the form of cash. An average fund experiences monthly net outflows of 0.265% of TNA and generates a slightly negative single-factor alpha of -0.006%. In Panel B, we report time-series distribution of the main market-wide variables: implied market volatility, VIX$_t$, market return, R_t^m, Hu, Pan, and Wang's (2013) noise measure, Noise$_t$, and TED spread, TedSpread$_t$.

4 Baseline Results and Empirical Strategy

4.1 Fragility and Active Liquidity Management

We begin by focusing on mutual fund liquidity management responses to the increased risk of fund fragility. To do so, we build on Chen et al. (2010), Goldstein et al. (2017), and Jin et al. (2022) and define markert stress periods, Stress$_t$ – i.e., times of increased market fragility – as year-months when VIX is above the 75th percentile of the sample in a given month (e.g., Rey, 2015; Jin et al., 2022). Our empirical strategy explores heterogeneity in mutual fund exposure to market-wide risk. According to recent empirical studies, fragility risk is amplified among less liquid funds and/or funds held by unsophisticated investors (Chen et al., 2010; Goldstein et al., 2017). We empirically investigate the impact of various measures of fragility on active liquidity management by estimating versions of the following regression model:

$$\mathrm{ALMgmt}_{f,t} = \beta_1 \mathrm{Fragility}_{f,t-1} \times \mathrm{Stress}_t + \beta_2 \mathrm{Fragility}_{f,t-1} + \mathrm{X}'_{f,t-1}\Gamma_1 + \mathrm{G}_f + \mathrm{G}_t + \epsilon_{f,t}, \quad (6)$$

where Stress$_t$ is an indicator variable for market stress, as defined above, and Fragility$_{f,t-1}$ is one of our measures of fund-specific fragility or peer fragility; this is an indicator variable that takes the value of one if the fund is in the top quartile of the corresponding fragility

[7] We obtain the value of 12% from assigning illiquidity ranks between zero and one for all stocks every month and estimate a fund-level illiquidity rank.

proxy. $X_{f,t-1}$ is a vector of fund-specific, time-varying controls that includes the natural logarithm of TNAs, the fund's alpha, portfolio's volatility beta, the net-expense ratio, and Nanda and Wei's (2018) overlap management measure. G_f and G_t denote fund and year×month fixed effects, respectively.

The main coefficient of interest is β_1, which captures the differential reaction to episodes of stress between fragile and non-fragile funds. We report our regression estimates in Table 2. In columns (1) to (4), we focus on fund-specific CGJ fragility exposure: portfolio illiquidity, retail ownership, and illiquidity risk. The coefficient estimates on the interaction terms are negative and statistically significant. This suggests that fragile funds actively take measures to reduce the extent of the first-mover advantage among their investors by rebalancing their portfolio toward more liquid assets in times of market stress. The effect is also economically relevant. Funds with illiquid (high liquidity risk) portfolios increase the liquidity of their portfolio by 0.131 (0.165) standard deviation in highly volatile times compared to funds with less fragile portfolios. Also, funds held predominantly by retail investors increase the liquidity of their portfolio by 0.06 standard deviation in times of market stress.

Our regression analysis is saturated with unrestricted fund and year×month fixed-effects in an attempt to remove as many fund-specific unobserved factors and market-wide shocks as possible. Fund fixed effects allow us to control for time-invariant differences between fragile and non-fragile funds, such as redemption fees, investor composition, or investment focus. Thus, the fund dummies allow us to ensure that general liquidity preferences or managerial quality are not driving our results. By controlling for time fixed effects, we can rule out a potential concern that we document a market-wide demand for liquidity during highly volatile times, as documented previously in the literature (Ben-Rephael, 2017; Rzeźnik, 2025). Year×month fixed effects also allow us to control for aggregate shocks and common trends in investors' flows, which, among others, include market-fear-induced outflows or investor sentiment.

Next, we investigate whether the exposure to peers' fragility affects mutual fund liquidity preferences. We use our two proxies of peers' fragility: retail ownership of peer funds, Peer $\text{Retail}_{f,t-1}$, and a fund's exposure to fire sales of other funds through common share ownership, Peer $\text{FtS}_{f,t-1}$. We examine the impacts of peer fragility on mutual fund liquidity management by re-estimating the Equation (6), where $\text{Fragility}_{f,t-1}$ is one of our peer fragility measures. We report our regression estimates in Table 2 columns (5) to (7). Both interaction term coefficients are negative and highly statistically significant, suggesting that mutual funds actively rebalance their portfolio toward more liquid stocks when exposed to fragility among their peers in times of market stress. Mutual funds that hold stocks, which are likely to experience substantial fire-sale price pressure due to extreme outflows from other funds, increase the liquidity of their portfolio by 0.226 standard deviations in times of market stress. We also observe a 0.085 standard deviation shift toward liquid stocks during high volatility times for funds, whose peers are predominantly retail-oriented, and thus more exposed to the first-mover advantage in sales of common holdings.

To ensure that the peer fragility proxies do not simply capture fund's own fragility, we include both CGJ and peer fragility measures in column (8) of Table 2. All coefficient estimates on the interaction terms are negative and statistically significant, implying that each of the fragility measures reflects a somewhat different dimension of a fund's fragility. These results also suggest that peer fragility has its own independent impact on a fund's portfolio composition above and beyond the effect of strategic complementarities among investors on funds' liquidity preferences.

Finally, we combine the fund-specific and peer fragility measures into two indices: Fragility $\text{Index}_{f,t-1}$ and Peer $\text{Index}_{f,t-1}$, respectively. The two indices capture different features of fund fragility and also allow for interactions between single fragility proxies. For example, low liquidity of the fund's portfolio in times of market stress may create the first-mover advantage in the redemption decision, but if the fund ownership is mostly composed of institutional investors, the first-mover advantage may be alleviated. When we relate the active liquidity management measure to Fragility $\text{Index}_{f,t-1}$ and Peer $\text{Index}_{f,t-1}$ interacted with market stress dummy in column (9), we find that, in times of market stress, mutual funds actively increase the liquidity of their portfolio by 0.113 and 0.124 standard deviation for a one standard deviation increase in Fragility $\text{Index}_{f,t-1}$ and Peer $\text{Index}_{f,t-1}$. These results provide initial support for Hypothesis 1 that fund managers respond to the peer fragility with the same degree of portfolio rebalancing in terms of liquidity as they react to the fund-specific strategic complementarities among investors.

4.2 Fragility and Investor Flows

Though mutual funds respond to their peer and own fragility in a similar manner, the underlying mechanisms driving these responses are quite different. In case of CGJ fragility, funds use active liquidity management as a device that is supposed to reduce the first-mover advantage and the amplification of investor outflows. In contrast, the peer fragility is unlikely to have a direct effect on fund flows, but potentially can negatively impact the value and liquidity of fund holdings and thus, prompt a fund manager to rebalance her portfolio toward more liquid assets. According to our Hypothesis 2, if our peer fragility measures indeed capture a fund's exposure to peer fragility and not its own degree of strategic complementarities among investors, we should observe no relationship between a fund's flows and the peer fragility measures.

We empirically examine the relationship between investor flows and the fragility measures in the same regression model as Equation (6), where we use mutual fund net flows as a dependent variable. We report our regression estimates in Table 3. In columns (1) to (4), we confirm the findings of Chen et al. (2010) and Goldstein et al. (2017) that funds more exposed to strategic complementarities among their investors experience greater outflows in times of market stress. Both the retail ownership composition and illiquidity of a fund portfolio amplify redemption obligations during market stress. Next, we investigate whether peer fragility contributes to intensified investor withdrawals as well. We report our regression estimates in columns (5) – (7). The coefficient estimates of both interaction terms Peer $\text{FtS}_{f,t-1} \times \text{Stress}_t$ and Peer $\text{Retail}_{f,t-1} \times \text{Stress}_t$ are insignificant. Also, when we combine both peer fragility measures into a single peer index in column (9), we observe no relationship between fund flows and the index. On the other hand, the interaction term between Stress_t and Fragility $\text{Index}_{f,t-1}$ (composed of CGJ fragility proxies) is negative and highly statistically significant. These results lend support to our Hypothesis 2 that peer fragility measures are unrelated to investor flows and thus unlikely to proxy for the degree of strategic complementarities among investors. Given a strong managerial response in terms of liquidity to shifts in peer fragility, but no reaction of investor flows, it appears that peer fragility the fragility spill-over effects among mutual funds.

4.3 Market Stress and Fragility profiles

Our results suggest that mutual funds exposed to their own or peer fragility respond by increasing the liquidity of their portfolio during times of market stress. To understand how mutual fund liquidity preferences change with shifts in the degree of market stress and a fund's exposure to fragility, we estimate the following panel regression:

$$\begin{aligned} \mathrm{Y}_{f,t} &= \sum_{i=2}^{4}\sum_{g=2}^{7} \gamma_{ig} \text{Fragility Quartile}^{i}_{f,t-1} \times \mathrm{D}^{g}_{t} + \sum_{i=2}^{4} \gamma_{i} \text{Fragility Quartile}^{i}_{f,t-1} \\ &\quad + \mathrm{X}'_{f,t-1}\Gamma + \mathrm{G}_f + \mathrm{G}_t + \eta_{f,t}, \end{aligned} \tag{7}$$

where $\mathrm{Y}_{f,t}$ denotes either the fund's active liquidity management measure or investor flows. Fragility is either CGJ fragility index, Fragility Index$_{f,t-1}$, or peer fragility index, Peer Index$_{f,t-1}$. Fragility Quartile$^{i}_{f,t-1}$ is a dummy variable that takes a value of one if fund f's Fragility Index$_{f,t-1}$ (Peer Index$_{f,t-1}$) in month $t-1$ belongs to the ith quartile of Fragility Index (Peer Index) distribution, otherwise zero. We sort year-months into seven groups, capturing different degrees of market stress based on monthly VIX levels. We assign year-months with an average VIX between 10 and 15 points to the lowest stress group (D^{1}_{t}). We use increments of 5 points for each stress group. For VIX levels above 40 points, we assign year-months to the highest stress group (D^{7}_{t}). Thus, we compare average liquidity management and investor flows for each fragility quartile and the market stress group to the average liquidity preferences and fund flows for funds that belong to the lowest fragility quartile within the same market stress bin. So, for example, the γ_{47} coefficient compares liquidity preferences and net flows of mutual funds that belong to the top quartile of Peer Index during periods of high market stress (when VIX is greater than 40 points) to the liquidity management and investor flows of mutual funds in the bottom quartile of Peer Index during the same highly uncertain times. If our peer fragility index captures potential spillovers from fragile peer funds onto other funds and not strategic complementarities among investors, we would expect the demand for liquidity to amplify with increases in a fund's peer fragility and market volatility. At the same time, investor flows should remain unaffected by the fund's exposure to its peer fragility.

Panel A of Figure 2 plots γ_{ig} coefficients on the interaction terms between Fragility Index Quartile$^{i}_{f,t-1}$ and D^{g}_{t} in Panel A. In Panel B of Figure 2, we plot γ_{ig} coefficient estimates on Peer Index Quartile$^{i}_{f,t-1} \times \mathrm{D}^{g}_{t}$ together with 95% confidence intervals computed with standard errors clustered at the fund and year×month level. The orange diamonds (grey dots) represent coefficient estimates with active liquidity management (net flows) as an independent variable. Panel A of Figure 2 shows that investor withdrawals and liquidity preferences increase with rises in market volatility and when funds are more exposed to strategic complementarities among investors. It is apparent that both investor net flows and our measure of active liquidity measure monotonically decrease with the higher VIX and CGJ-fragility exposure. Funds belonging to the top quartile of Fragility Index distribution experience especially sizeable investor withdrawals in periods when VIX is above 20 points. For the same group of funds, we also observe an intensified shift toward more liquid stocks during volatile times.

These findings are consistent with the amplification of the first-mover advantage during market stress, especially for funds with a greater degree of strategic complementarities among investors documented by Chen et al. (2010) and Goldstein et al. (2017). The plotted coefficients also indicate that mutual funds actively and significantly rebalance their portfolios when subject to the first-mover advantage in investor redemption during market stress. Also, based on the observed patterns in the graph, we set the threshold for periods of market stress – VIX values above the 75th percentile of the sample – and the classification of fragile funds – in the top quartile of Fragility Index distribution.

In Panel B of Figure 2, we observe a similar response of mutual funds in terms of liquidity management to peer fragility during different market uncertainty periods. Mutual funds' liquidity preferences intensify especially for funds most exposed to peer fragility (top quartile) during high volatility periods. However, investor flows are not differentially impacted by the fund's peer fragility exposure. For each market volatility bin, the net flows of funds in high or medium Peer Index quartiles are indistinguishable from net-flows of funds in the bottom quartile. Thus, Figure 2 provides a visual representation of our working hypothesis, that there are (at least) two sources of mutual fund fragility. While fund-specific fragility indirectly affects mutual fund liquidity preferences through intensified investor withdrawals during stress time, peer fragility has a direct effect on a fund's liquidity management through common stock ownership. Consequently, mutual funds actively increase the liquidity of their portfolio to reduce the potential fragility due to both investor flows and the fund's peers.

Recent empirical studies by Chernenko and Sunderam (2016, 2020) document that mutual funds use cash holdings to internalize flow-induced price pressure. In Appendix A, we investigate the effect of CGJ and peer fragility on mutual fund cash holdings. Table A.1 shows that mutual funds use equity holdings rather than cash to increase the portfolio's liquidity in times of market stress and when exposed to financial fragility, consistent with (Rzeźnik, 2025).

4.4 Liquidity Management and Net-trading Analysis

To better understand how mutual funds with high exposure to CGJ and peer fragility increase the liquidity of their portfolio during times of market stress, we investigate the funds' net trading for different liquidity bins. By looking at the net trading for each liquidity bucket, we can assess whether funds increase the portfolio's liquidity by net-purchasing more liquid stocks or net-selling less liquid holdings. First, we sort portfolio holdings into six liquidity bins, l. The most liquid group ($l = 1$) consists of stocks, whose lagged Amihud measure is smaller than lagged mean portfolio liquidity $\text{Illiq}_{f,t-1}$, minus a one standard deviation of holdings liquidity of fund f in month $t-1$, $\sigma^{\text{Illiq}}_{f,t}$. The second most liquid group ($l = 2$) consists of stocks with lagged Amihud measure greater than $\text{Illiq}_{f,t-1} - \sigma^{\text{Illiq}}_{f,t}$, but smaller than $\text{Illiq}_{f,t-1} - \frac{1}{2}\sigma^{\text{Illiq}}_{f,t}$. The third group ($l = 3$) comprises stocks with lagged Amihud measure between $\text{Illiq}_{f,t-1} - \frac{1}{2}\sigma^{\text{Illiq}}_{f,t}$ and $\text{Illiq}_{f,t-1}$. The fourth, fifth, and sixth liquidity groups are constructed in an analogous way, meaning that the most illiquid bin ($l = 6$) includes stocks, whose lagged Amihud measure is greater than lagged mean portfolio liquidity plus a one standard deviation of holdings liquidity of fund f in month $t-1$, ($> \text{Illiq}_{f,t-1} + \sigma^{\text{Illiq}}_{f,t}$). Next, for each liquidity bin, we compute funds' net trading in the following way:

$$\text{Net-Trade}^{l}_{f,t} = \sum_{s=1}^{L} \frac{\text{Value of Buys}_{f,s,t} - \text{Value of Sells}_{f,s,t}}{\text{TNA}_{f,t-1}}, \tag{8}$$

where $\text{Value of Buys}_{f,s,t}$ ($\text{Value of Sells}_{f,s,t}$) is a dollar value of shares purchased (sold) of stock s by fund f over month t. L denotes the number of stocks traded by fund f in month t that belong to liquidity bin l. Finally, we examine how fragile funds increase the liquidity of their portfolio by estimating the following regression equation for each liquidity bin, l:

$$\begin{aligned}\text{Net-Trade}^{l}_{f,t} \;=\;& \gamma_1 \text{High Fragility Index}_{f,t-1} \times \text{Stress}_t + \gamma_2 \text{High Fragility Index}_{f,t-1} \\ & + \gamma_3 \text{High Peer Index}_{f,t-1} \times \text{Stress}_t + \gamma_4 \text{High Peer Index}_{f,t-1} \\ & + \text{X}'_{f,t-1}\Gamma + \text{G}_f + \text{G}_t + \eta^{l}_{f,t}. \end{aligned} \tag{9}$$

This regression design allows us to capture differential net-trading behaviour within the same liquidity bin during times of market stress between fragile and non-fragile funds. Figure 3 plots the γ_1 and γ_3 coefficient estimates together with 95% confidence intervals. The light-green-shaded areas illustrate liquidity-enhancing regression estimates, while light-red-shaded areas indicate the regions of coefficient estimates that result in decreased portfolio liquidity. The light-purple circles represent point estimates on the interaction term between peer fragility index and market stress, γ_3. The grey squares denote point estimates on the interaction between high CGJ fragility index and market stress, γ_1. High CGJ fragile funds increase their portfolio liquidity mainly through net-sells of the least liquid holdings. The coefficient estimates on High Fragility Index$_{f,t-1}$ $\times$ Stress$_t$ are negative and (marginally) significant for the least liquid bins ($l \in [4:6]$). This behaviour is in line with theoretical predictions of Brown et al. (2010), who show that "optimal liquidation involves selling strictly more of the assets with a lower ratio of permanent to temporary impact, even if these assets are relatively illiquid."

When we focus on the interaction term between High Peer Index$_{f,t}$ and Stress$_t$, we find a positive and significant γ_3 coefficient for the three top liquid bins. This suggests that funds with high peer fragility exposure increase the liquidity of their portfolio by net-purchasing more liquid stocks. In contrast to CGJ fragility, increased peer fragility does not result in investor redemptions; thus, funds exposed to peer fragility can increase the portfolio's liquidity by net-purchasing more liquid stocks.

5 Further Evidence from Quasi-natural Experiments

5.1 Evidence from Volatility Shocks

So far, our panel-regression-based analysis exploits the differential behaviour of mutual funds subject to financial fragility – top fragility quartile funds compared to funds in the middle and the bottom quartiles – during market stress times – high *magnitude* VIX compared to low. As an alternative identification strategy, we conduct a panel event study analysis that takes advantage of sudden *jumps* in the VIX, which we call 'volatility shocks.' In particular, we consider any monthly change in the VIX greater than a standard deviation to be a 'shock.' During our sample period, there are six such events, as depicted in Figure 4. Each of these shocks corresponds to a well-known financial crisis as labelled in the figure. These include the global financial crisis, the European debt crisis, the downgrade of the credit ratings of the US federal government, the Taper Tantrum, and the COVID-19 pandemic-induced volatility.

In our event study design, we use a short window to focus exclusively on mutual fund responses in terms of liquidity and investor flows induced by sudden and unexpected jumps in market volatility. Specifically, we take four periods before and after the volatility shock and centre them on date zero – the month of the volatility shock. We then 'stack' each of our event-specific panels and estimate regressions of the following form:

$$
\begin{aligned}
\mathrm{Y}_{f,e,g} = & \sum_{e=-4,e\neq-1}^{4} \alpha_e \text{High Fragility Index}_{f,e,g} \times \mathrm{D}(e)_g \\
& + \sum_{e=-4,e\neq-1}^{4} \beta_e \text{High Peer Index}_{f,e,g} \times \mathrm{D}(e)_g + \mathrm{X}'_{f,e-1,g}\Lambda + \mathrm{G}_{f,g} + \mathrm{G}_{e,g} + \varepsilon_{f,e,g}
\end{aligned} \tag{10}
$$

where $\mathrm{Y}_{f,e,g}$ is either the active liquidity management measure or investor flows for fund f in relative-time e for volatility-shock event g depicted in Figure 4. $\mathrm{D}(e)_g$ is a dummy variable equal to one exactly e months after (or before if e is negative) the initial g volatility shock. $\mathrm{X}_{f,e-1,g}$ is the same set of controls as defined previously, and $\mathrm{G}_{f,g}$ and $\mathrm{G}_{e,g}$ denote a complete set of shock-event fund and year×month fixed effects, respectively. The coefficients of interest are α_{-4} to α_4 and β_{-4} to β_4 which denote the differential active liquidity management or fund net flows between (peer) fragile and non-fragile funds in the periods directly before and after the volatility shock. We use a month prior to the volatility jump ($e = -1$) as a reference period. As discussed in Baker, Larcker, and Wang (2022), this 'stacked' regression estimation strategy estimates event-specific coefficients and uses variance weighting to combine them.[8]

We plot the regression estimates from Equation (10) together with 95% (light-red area) and 90% (dark-red area) confidence intervals in Figure 5. The top two panels show the portfolio rebalancing in terms of liquidity by funds exposed to strategic complementarities among investors (top-left) and to peer fragility (top-right) around a volatility shock. In the bottom two panels, we plot coefficient estimates from net flow regressions.

The event study results are consistent with the panel-regression-based evidence. Fragile mutual funds actively rebalance their portfolio toward more liquid stocks in response to a negative market stress shock. Regardless of whether the fund fragility comes from investor flows or from the peers, fund managers significantly increase the liquidity of their portfolio during the months coinciding with and immediately following the volatility jump. The effect of the volatility shock on the liquidity preferences of fragile funds

[8] See also Cengiz, Dube, Lindner, and Zipperer (2019); Goodman-Bacon (2021); Sun and Abraham (2021); Callaway and Sant'Anna (2021); Roth, Sant'Anna, Bilinski, and Poe (2023) for estimation strategies with staggered adoption and heterogeneity in two-way fixed-effects settings. Following the recommendation of Baker et al. (2022), we use the stacked estimation strategy as a baseline which allows us to transparently estimate the coefficients on both the High Fragility $\text{Index}_{f,e,g}$ and High Peer $\text{Index}_{f,e,g}$ in a regression set-up. However, in Appendix A Figure A.1 we also implement the approach of Callaway and Sant'Anna (2021) and obtain very similar results.

is also economically relevant. We find that funds subject to CGJ fragility increase the liquidity of their portfolio by -0.3 standard deviations during the event month and by -0.1 standard deviations in the first month following the volatility event, relative to non-CGI fragile funds. For funds with high-peer fragility, these figures are -0.1 and -0.1 for the first and second months, respectively, relative to non-peer fragile funds. Note that these are marginal effects; the coefficients for CGJ fragility are estimated holding peer fragility constant and likewise for the coefficients on peer fragility. Similar to panel-regression-based results, we also observe that funds subject to strategic complementarities among investors experience an increase in redemption obligations by -0.1 standard deviation in the first two months since the initial volatility shock. The exposure to peer fragility seems not to have any effect on investor flows.

5.2 Evidence from the 2003 Mutual Fund Scandal

Up until this point, our results indicate that during times of crises, mutual funds shift the composition of their holdings toward more liquid stocks in order to reduce the fragility of their portfolio stemming from strategic complementarities among fund's own investors and the exposure to their peers' fragility. Though times of market stress are frequently used in the analysis of mutual fund fragility (e.g., Chen et al., 2010; Goldstein et al., 2017; Jin et al., 2022), they may coincide with unobservable changes in fund's investment opportunity set which, in turn, might be correlated with the degree of fragility of fund's peers.

To address this potential concern, we explore the 2003 mutual fund late trading scandal that resulted in unexpected investor withdrawals from scandal-implicated mutual funds. Following Antón and Polk (2014), and Falato et al. (2021), we consider investor redemptions due to the scandal as an exogenous shock, which allows us to examine both liquidity preferences and investor flows of *non-scandal* funds, whose peers were participating in illegal activities involving late trading and market timing. The outbreak of the mutual fund trading scandal provides an appealing shock because it takes place in otherwise 'calm' market times and non-scandal funds are unlikely to experience any fragility coming from their own investors, but may be differentially exposed to scandal-induced peer fragility.

To measure funds' exposure to peer fragility stemming from the scandal, we first construct imputed outflows at the stock-time level. For each stock i, we compute a weighted average of outflows from publicly-known scandal-implicated funds s that held the stock at the end of a previous month, where weights are defined by the volume of scandal-implicated funds' holdings of stock i. Formally, the imputed outflow of stock i at date t is given by:

$$\text{Imputed Outflows}_{i,t} = \sum_{s=1}^{N} \frac{\text{Shares Held}_{i,s,t-1}}{\sum_{s=1}^{N} \text{Shares Held}_{i,s,t-1}} \cdot \text{Outflows}_{s,t}, \tag{11}$$

where Shares $\text{Held}_{i,s,t-1}$ is a number of shares held of stock i by scandal-involved fund s at the end of month $t-1$ and $\text{Outflows}_{s,t}$ denote investor withdrawals from publicly-known scandal-implicated fund s over month t. Then, we aggregate stock-specific Imputed $\text{Outflows}_{i,t}$ into a portfolio level for each non-scandal fund:

$$\text{Imputed Outflows}_{f,t} = \sum_{i=1}^{S} \omega_{i,f,t} \cdot \text{Imputed Outflows}_{i,t}, \quad f \notin \text{scandal-implicated fund.} \tag{12}$$

Finally, we define a dummy variable, High Peer Scandal $\text{Exposure}_{f,t}$, that takes a value of one if Imputed $\text{Outflows}_{f,t}$ of non-scandal fund f in month t belong to the bottom quartile of Imputed $\text{Outflows}_{f,t}$ distribution, otherwise zero.

We first visually assess how non-scandal mutual funds respond to scandal-induced outflows from their peers. For each non-scandal fund, we compute an average exposure to scandal-induced fragility from September 2003 to December 2004:

$$\overline{\text{Imputed Outflows}}_{f} = \frac{1}{T} \sum_{t=\text{Sep 2003}}^{T=\text{Dec 2004}} \text{Imputed Outflows}_{f,t}. \tag{13}$$

We follow Yagan (2019) and depict the effect of $\overline{\text{Imputed Outflows}}_{f}$ in each month on mutual fund liquidity preferences. Every month t, we subtract from fund's active liquidity management measure the pre-scandal outbreak average (averaged over the September 2002 to August 2003 period). Then, we run cross-sectional regressions of demeaned active liquidity management measure on $\overline{\text{Imputed Outflows}}_{f}$ and plot the resulting regression coefficients together with 95% confidence intervals in Figure 6, where we smooth the coefficients over 3-month window to avoid our results being clouded by high-frequency fluctuations. In each of the cross-sectional regressions, we control for fund's lagged portfolio liquidity, alpha, log of TNA, portfolio's volatility beta, expenses, Nanda and Wei's (2018) overlap management measure, and contemporaneous fund net-flows.

As we can see from Figure 6, the coefficient estimates on $\overline{\text{Imputed Outflows}}_{f}$ (grey dots) fluctuate around zero during the pre-scandal outbreak period. After the initial scandal outbreak in September 2003, $\overline{\text{Imputed Outflows}}_f$ coefficient estimates become negative and significant, indicating that non-scandal mutual funds actively increase the liquidity of their portfolio when exposed to outflows of scandal-implicated funds through common stock ownership. Though they are not directly affected by the scandal news, they attempt to offset the fragility stemming from peers' redemptions by increasing their portfolio's liquidity and thus bringing down the overall degree of fragility. The statistically significant shift toward more liquid stocks coincides with the intensity of scandal-related news. We depict the scandal-related news intensity with orange bars that represent the number of newly-reported funds involved in the late trading scandal in a given month.

Given the initial visual inspection in Figure 6, we investigate the relationship between non-scandal funds' liquidity preferences and their exposure to scandal-induced peer fragility in the regression framework. We examine how *non-scandal* funds actively manage the liquidity of their portfolio in the twelve months following the initial scandal outbreak (from September 2003 to August 2004) in the following way:

$$\text{ALM}\textsc{gmt}_{f,t} = \beta_1 \text{High Peer Scandal Exposure}_{f,t} + \text{X}'_{f,t-1}\Gamma_1 + \textsc{g}_f + \textsc{g}_t + \varepsilon_{f,t}, \tag{14}$$

where $\text{X}_{f,t-1}$ is a vector of one-month lagged fund-specific time-varying controls. We report the regression estimates in columns (1) and (2) of Table 4. The coefficient estimate on High Peer Scandal $\text{Exposure}_{f,t}$ is negative and statistically significant, indicating that non-scandal funds with high exposure to scandal-induced peer fragility actively increase their demand for liquidity by 0.2 standard deviation compared to less exposed non-scandal funds during the twelve months subsequent the initial scandal outbreak.

To understand the underlying mechanisms driving funds' liquidity preference in response to scandal-induced peer fragility, we relate investor flows of non-scandal funds to High Peer Scandal $\text{Exposure}_{f,t}$ by re-estimating Equation (14) with net-flows as a dependent variable. We report the regression estimates in columns (3) and (4) of Table 4. In both specifications, the coefficient estimates on High Peer Scandal $\text{Exposure}_{f,t}$ are insignificant in the net-flows regressions, which is consistent with our previous results. Mutual funds aim to counteract negative externalities imposed by peer fragility on a portfolio's performance and liquidity by shifting their portfolio toward more liquid assets. However, peer fragility does not directly affect fund flows, in contrast to a fund's own fragility that makes itself manifest through amplified investor withdrawals (Chen et al., 2010; Goldstein et al., 2017).

5.3 Evidence from the Great Recession

Next, we want to ensure that our results are not subject to the "reflection problem" (Manski, 1993), which boils down to a potential endogeneity problem: the exposure to peer fragility is endogenously related to fund characteristics, so the challenge is to differentiate between fund's liquidity management in response to a shock to fragility of fund's peers from portfolio rebalancing due to changes in fundamentals or other confounding factors that may affect fund's liquidity preferences. To do so, we examine a "shift-share" treatment that exploits peers' differential exposure to financial crises in 2008.

5.3.1 Mutual Fund Responses to Peer Fragility Exposure

We build on Hau and Lai (2017), who investigate portfolio allocation decisions of distressed equity funds during the recent financial crises. The authors show that distressed funds – i.e., funds experiencing considerable losses in financial stocks – used non-financial best-performing stocks to meet investor withdrawals, which contributed to crisis propagation. This implies that funds holding a greater portion of their portfolio in financial stocks were more exposed to financial crises and thus more fragile. Conditional on the fund's own exposure to the crises, funds, whose peers hold financial stocks to a larger extent, are potentially subject to peer fragility. We apply Bhattacharya, Lee, and Pool's (2013) $\textsc{Overlap}_{f,j,t}$ measure to determine fund's peers, but use two definitions of fund's portfolio: one that includes both financial and non-financial stocks and the other one that comprises only non-financial stocks.[9] We capture fund's own exposure to financial crises by computing a percentage of fund f's portfolio invested in 'financial stocks' in a given month, Own $\text{Exposure}_{f,t}$. NF Peer $\text{Exposure}_{f,t}$ is fund f's exposure to peer financial crises fragility in month t. To determine funds' closest peers, we choose 20 funds with the highest non-financial-holding-based $\textsc{Overlap}$ value with fund f. Then, we calculate the average percentage of financial stocks in a portfolio of fund f's peers, NF Peer $\text{Exposure}_{f,t}$. Peer $\text{Exposure}_{f,t}$ is calculated in the same way, but uses the entire mutual fund portfolio to compute the $\text{Overlap}_{f,j,t}$ measure.

[9]We follow Hau and Lai (2017) and defined the following six industries exposed to the financial crises ('financial stocks'): Banks (SIC codes: 6000, 6010-6036, 6040-6062, 6080-6082, 6090-6113, 6120-6179, and 6190-6199), Insurance (SIC codes: 6300, 6310-6331, 6350-6351, 6360-6361, 6370-6379, and 6390-6411), Real estate (SIC codes: 6500, 6510, 6512-6515, 6517-6532, 6540-6541, 6550-6553, and 6590-6611), Financial Trading (SIC codes: 6200-6299, 6700, 6710-6726, 6730-6733, 6740-6779, 6790-6795, and 6798-6799), and Building Materials (SIC Codes: 0800-0899, 2400-2439, 2450-2459, 2660-2661, 2950-2952, 3200, 3240-3241, 3250-3259, 3261-3261, 3264-3264, 3270-3275, 3280-3281, 3290-3293, 3295-3299, 3420-3423, 3440-3442, 3446, 3448-3452, 3490-3499, 3996), and Construction (SIC Codes: 18, 1500-1511, 1520-1549, 1600-1799).

We examine mutual fund liquidity preferences and investor flows around the Lehman Brothers' collapse in the following panel regression:

$$\begin{aligned} \mathrm{Y}_{f,t} \;=\; & \sum_{c=-10,\, c\neq -1}^{10} \rho_c \text{NF Peer High Exposure}_{f,t-1} \times \mathrm{D}(c)_t \\ & + \mathrm{X}'_{f,t-1}\Gamma_1 + \mathrm{G}_f + \mathrm{G}_t + \eta_{f,t}, \end{aligned} \tag{15}$$

where $\mathrm{Y}_{f,t}$ is either active liquidity management measure or investor flows. $\mathrm{D}(c)_t$ is an indicator variable equal to one exactly c months after (or before if c is negative) the Lehman Brothers' collapse (in September 2008, $c = 0$). NF Peer High Exposure$_{f,t-1}$ is a dummy variable that takes a value of one if fund f's NF Peer Exposure$_{f,t-1}$ belongs to the top quartile, otherwise zero. $\mathrm{X}_{f,t-1}$ includes the interaction term between fund's own exposure to financial crises, Own High Exposure$_{f,t-1}$, and the post Lehman Brothers' collapse dummy variable on top of the set of control variables previously defined. Own High Exposure$_{f,t-1}$ is a dummy variable that takes a value of one if fund f's Own Exposure$_{f,t}$ belongs to the top quartile, otherwise zero. G_f and G_t denote a complete set of fund and year×month fixed effects, respectively. The coefficient of interest are ρ_{-10} to ρ_{10}. They capture the differential effect of liquidity management or fund net flows between funds with high and low peer exposure to financial crises in the periods directly before and after the bankruptcy of Lehman Brothers. We use August 2008 (one month prior to the collapse, $c = -1$) as a reference month.

We plot the regression estimates from Equation (15) together with 95% (light-red area) and 90% (dark-red area) confidence intervals in Figure 7. The left panel shows the coefficient estimates from a regression with active liquidity management as a dependent variable. The right panel plots the coefficient estimates from a regression with mutual fund net flows as a dependent variable. Both panels show that mutual funds with high peer exposure to financial crises do not significantly differ, in terms of liquidity preferences and investor flows, from low-exposure funds before the collapse of Lehman Brothers. However, funds with peers highly exposed to financial stocks actively increase the liquidity of their portfolio after September 2008 compared to low-exposure funds. The ρ_1 to ρ_{10} coefficient estimates are all negative and become statistically significant in March 2009. While mutual funds respond to peer financial crises exposure, their net flows remain unaffected. The right panel shows that all coefficient estimates in net-flows regression are insignificant. The lack of flow responses to peer fragility is consistent with our previous results from panel-based regression, event study, and the 2003 trading scandal and suggests that peer fragility is not just another proxy for strategic complementarities among investors, but an independent source of financial fragility.

We also investigate mutual fund active liquidity management around Lehman Brothers' collapse in a standard diff-in-diff estimation framework:

$$\text{ALMgmt}_{f,t} = \rho + \rho_1 \text{(NF) Peer High Exposure}_f \times \text{Post}_t + \text{X}'_{f,t-1}\Gamma_1 + \text{G}_f + \text{G}_t + \eta_{f,t} \quad (16)$$

where (NF) Peer High Exposure$_f$ is a dummy variable that takes a value of one if the average of fund f's peer exposure to financial stocks before the Lehman Brothers collapse belongs to the top quartile, otherwise zero. Post$_t$ is an indicator variable that takes a value of one after the fall of Lehman Brothers. $\text{X}_{f,t-1}$ includes the interaction term between fund's own exposure to financial crises and the post Lehman Brothers' collapse dummy variable on top of the set of control variables previously defined.

We report regression estimates in Table 5. In columns (1) to (4), we define funds' peers as 20 funds with the highest Overlap value with the fund, where the Overlap measure is computed using both financial and non-financial holdings. In columns (5) to (8), we define fund's peers as 20 funds with the highest Overlap value with the fund, where the Overlap measure is computed using only non-financial holdings. Regardless of our peer definition, we observe a negative and statistically significant coefficient on the interaction term between (NF) Peer Exposure and Post. While we control for funds' own exposure to the Great Recession, we find that, after the collapse of Lehman Brothers, funds highly exposed to peer financial fragility actively increase the liquidity of their portfolio by 0.335 standard deviation (columns (6)). Also, when we use a continuous measure of peer financial fragility (in columns (4) and (6)), we observe similar mutual fund responses in terms of liquidity. Thus, funds try to reduce the peer fragility of their portfolios by rebalancing their portfolio toward more liquid stocks. Next, we investigate whether funds' increased demand for liquidity due to their peer fragility exposure affects the prices of assets.

5.3.2 Peer Fragility and Stock Returns

Recent empirical literature documents that mutual funds were likely to propagate the financial crises by retaining the 'toxic' securities and liquidating a part of their portfolio less affected by the crises to reduce the cost of investors' withdrawals. This, in turn, exerted a negative price pressure on 'non-toxic' securities held by mutual funds with high exposure to financial crises (see e.g., Manconi et al., 2012; Hau and Lai, 2017). Our results, so far, show that mutual funds actively increase the liquidity of their portfolio in response to not only strategic complementarities among their investors but also the fragility of their peers. We, therefore, investigate how the increased demand for liquidity due to the rise in peer fragility affects stock prices.

We focus on a subset of *non-financial* stocks and examine their quarterly abnormal returns around September 2008 – the collapse of Lehman Brothers. First, we construct a stock-specific time-varying measure that captures a stock's fragility due to mutual funds' ownership and their portfolios' *direct* exposure to financial stocks prior to the Lehman Brothers bankruptcy (from July 2007 to June 2008):

$$\text{Own Exposure}_{i,t} = \sum_{f=1}^{N} \frac{\text{Shares Held}_{i,f,t-1}}{\sum_{f=1}^{N} \text{Shares Held}_{i,f,t-1}} \cdot \text{Own Exposure}_{f,t}, \tag{17}$$

where Own $\text{Exposure}_{f,t}$ is a percentage of fund f's portfolio invested in financial stocks at the end of month t. We measure a stock's *indirect* fragility stemming from the peer fragility exposure of the funds holding the stock in an analogous way:

$$\text{NF Peer Exposure}_{i,t} = \sum_{f=1}^{N} \frac{\text{Shares Held}_{i,f,t-1}}{\sum_{f=1}^{N} \text{Shares Held}_{i,f,t-1}} \cdot \text{NF Peer Exposure}_{f,t}, \tag{18}$$

where NF Peer $\text{Exposure}_{f,t}$ is an average percentage of fund f's closest peers' portfolio invested in financial stocks at the end of month t. For each quarter between July 2007 and June 2009, we run the following cross-sectional regression:

$$\text{AR}_i = \gamma_1 \text{NF Peer High Exposure}_i + \gamma_2 \text{Own High Exposure}_i + \text{X}_i' \Gamma + \text{G}_c + \zeta_i, \tag{19}$$

where AR_i is Carhart's (1997) four-factor abnormal return of stock i over a quarter q (between the third quarter of 2007 and the second quarter of 2009). NF Peer High Exposure_i is a dummy variable that takes a value of one if stock's average own exposure (over July 2007 to June 2008 period) belongs to the upper quartile of NF Peer $\text{Exposure}_{i,t}$ distribution, and zero otherwise. Own High Exposure_i is an indicator variable that takes a value of one if stock's average peer exposure (over July 2007 to June 2008 period) belongs to the upper quartile of Own $\text{Exposure}_{i,t}$ distribution, otherwise zero. X_i denotes a vector of stock-specific control variables defined prior to the Lehman Brothers collapse that includes the stock's average market capitalization, mutual fund ownership of shares over the number of shares outstanding, and the number of mutual funds holding the stock. In each cross-sectional regression, we also include industry fixed effects, G_c, and cluster the standard errors at the industry level.

We report our regression estimates in Table 6. Both coefficient on NF Peer High Exposure$_i$ and Own High Exposure$_i$ are insignificant for the first four quarters preceding the collapse of Lehman Brothers. Stocks held by funds with high own and/or peer exposure to yet-to-be-realized financial crises-induced fragility do not perform differently before the onset of the financial crises. This suggests that mutual funds with high own and/or peer fragility were neither better nor worse in selecting non-financial stocks before the fall of Lehman Brothers. Also, the pre-crisis performance of non-financial stocks with high own and/or peer mutual fund fragility was unlikely to negatively affect the performance of funds holding the stocks. However, once the fall of Lehman Brothers takes place, we observe negative and statistically significant coefficients on NF Peer High Exposure$_i$ and Own High Exposure$_i$ in the first two quarters since the collapse of Lehman Brothers. Thus, stocks held by mutual funds with high own exposure to financial crises underperform other non-financial stocks by 7.040 (7.503)bps or by 0.19 (0.17) standard deviation in the third (fourth) quarter of 2008. Also an increased exposure of mutual funds to fragility of their peers seems to exert a significant and negative price pressure on stock returns. Non-financial stocks held by funds with peers highly exposed to financial crises underperform other non-financial stocks by 12.068 (8.057)bps or 0.33 (0.18) standard deviation in the third (fourth) quarter of 2008. The underperformance of stocks with NF Peer High Exposure$_i$ and Own High Exposure$_i$ coincides with mutual funds trying to cope with the drawbacks of strategic complementarities among their investors and their peers, by actively increasing liquidity of their portfolio (see Figure 7).

6 Conclusions

The role of non-bank financial intermediaries in the stability of financial markets has recently drawn increased attention from policy makers (e.g., SEC, 2016; FSB, 2017). We contribute to this discussion by proposing a new 'interconnectedness' channel through which vulnerabilities among mutual funds can spill over to other funds and potentially contribute to increased financial fragility in equity markets. Specifically, we study mutual fund responses to the threat of peer withdrawal spillovers and the consequences of their actions.

We find that mutual funds facing high CGJ and peer fragility mitigate the threat by actively rebalancing their portfolio toward more liquid stocks during episodes of market stress. However, the mechanism underlying this behaviour is quite different. CGJ fragility is caused by strategic complementarities among investors that affect mutual fund liquidity preferences through amplified investor withdrawals in times of market stress. Peer fragility-driven liquidity demand, though, does not stem from redemption obligations. Instead, linkages through common stock ownership may impose negative externalities on the portfolio's performance and liquidity.

We evaluate the consequences of the increased demand for liquidity among mutual funds during times of market stress on the prices of stocks. We document that stocks held by funds with a greater exposure to peer fragility experience transitory negative price pressure following the collapse of Lehman Brothers. This result is robust to the inclusion of the average financial crisis exposure of funds holding the stock, market capitalization, mutual fund ownership, and industry fixed effects.

Overall, our paper suggests that interconnectedness among mutual funds can contribute to increased demand for liquidity in times of financial distress, when liquidity demands have already been elevated, and thus, has a destabilizing effect on market prices.

References

Acharya, V. V. and L. H. Pedersen (2005). Asset pricing with liquidity risk. *Journal of Financial Economics 77*(2), 375–410.

Amihud, Y. (2002). Illiquidity and stock returns: cross-section and time-series effects. *Journal of Financial Markets 5*(1), 31–56.

Ang, A., R. J. Hodrick, Y. Xing, and X. Zhang (2006). The Cross-Section of Volatility. *Journal of Finance 61*(1), 259–299.

Antón, M. and C. Polk (2014). Connected stocks. *Journal of Finance 69*(3), 1099–1127.

Asness, C. S., A. Frazzini, and L. H. Pedersen (2019). Quality minus junk. *Review of Accounting Studies 24*, 34—112.

Baker, A. C., D. F. Larcker, and C. C. Wang (2022). How much should we trust staggered difference-in-differences estimates? *Journal of Financial Economics 144*(2), 370–395.

Ben-Rephael, A. (2017). Flight-to-liquidity, market uncertainty, and the actions of mutual fund investors. *Journal of Financial Intermediation 31*(1), 30–44.

Bhattacharya, U., J. H. Lee, and V. K. Pool (2013). Conflicting Family Values in Mutual Fund Families. *Journal of Finance 68*(1), 173–200.

Blocher, J. (2016). Network externalities in mutual funds. *Journal of Financial Markets 3*, 1–26.

Brown, D. B., B. I. Carlin, and M. S. Lobo (2010). Optimal Portfolio Liquidation with Distress Risk. *Management Science 56*(11), 1997–2014.

Brunnermeier, M. K. and L. H. Pedersen (2009). Market liquidity and funding liquidity. *Review of Financial Studies 22*(6), 2201–2238.

Callaway, B. and P. H. Sant'Anna (2021). Difference-in-differences with multiple time periods. *Journal of Econometrics 225*(2), 200–230. Themed Issue: Treatment Effect 1.

Carhart, M. M. (1997). On persistence in mutual fund performance. *Journal of Finance 52*(1), 57–82.

Cengiz, D., A. Dube, A. Lindner, and B. Zipperer (2019, 05). The Effect of Minimum Wages on Low-Wage Jobs. *The Quarterly Journal of Economics 134*(3), 1405–1454.

Chen, Q., I. Goldstein, and W. Jiang (2010). Payoff complementarities and financial fragility: Evidence from mutual fund outflows. *Journal of Financial Economics 97*(2), 239–262.

Chernenko, S. and A. Sunderam (2016). Liquidity transformation in asset management: evidence from the cash holdings of mutual funds. *NBER Working Paper 22391*, 1–42.

Chernenko, S. and A. Sunderam (2020). Do Fire Sales Create Externalities? *Journal of Financial Economics 135*(3), 602–628.

Chordia, T., S.-W. Huh, and A. Subrahmanyam (2009). Theory-based illiquidity and asset pricing. *Review of Financial Studies 22*(9), 3629–3668.

Chung, K. H. and C. Chuwonganant (2014). Uncertainty, market structure, and liquidity. *Journal of Financial Economics 113*(3), 476–499.

Dyakova, T. and M. Verbeek (2013). Front-running of mutual fund fire-sales. *Journal of Banking and Finance 37*(12), 4931–4942.

Falato, A., A. Hortaçsu, D. Li, and C. Shin (2021). Fire-Sale Spillovers in Debt Markets. *Journal of Finance 76*(6), 3055–3102.

FSB (2017). Policy Recommendations to Address Structural Vulnerabilities from Asset Management Activities.

Goldstein, I., H. Jiang, and D. T. Ng (2017). Investor flows and fragility in corporate bond funds. *Journal of Financial Economics 126*(3), 592—613.

Goodman-Bacon, A. (2021). Difference-in-differences with variation in treatment timing. *Journal of Econometrics 225*(2), 254–277. Themed Issue: Treatment Effect 1.

Hasbrouck, J. (2009). Trading costs and returns for U.S. equities: Estimating effective costs from daily data. *Journal of Finance 64*(3), 1445–1477.

Hau, H. and S. Lai (2017). The role of equity funds in the financial crisis propagation. *Review of Finance 21*(1), 77–108.

Hu, G. X., J. Pan, and J. Wang (2013). Noise as information for illiquidity. *Journal of Finance 68*(6), 2341–2382.

Huang, J. (2020). Dynamic liquidity preferences of mutual funds. *Quarterly Journal of Finance 10*(4), 1–44.

Jiang, H., D. Li, and A. Wang (2021). Dynamic liquidity management by corporate bond mutual funds. *Journal of Financial and Quantitative Analysis 56*(5), 1622–1652.

Jin, D., M. Kacperczyk, B. Kahraman, and F. Suntheim (2022). Swing pricing and fragility in open-end mutual funds. *Review of Financial Studies 35*(1), 1–50.

Kisin, R. (2011). The impact of mutual fund ownership on corporate investment: Evidence from a natural experiment. *Olin Business School Working Paper*, 1–40.

Manconi, A., M. Massa, and A. Yasuda (2012). The role of institutional investors in propagating the crisis of 2007–2008. *Journal of Financial Economics 104*(3), 491–518.

Manski, C. F. (1993). Identification of Endogenous Social Effects: The Reflection Problem. *Review of Economics Studies 60*(3), 531–542.

Massa, M., D. Schumacher, and Y. Wang (2021). Who Is Afraid of BlackRock? *Review of Financial Studies 34*(4), 1987–2044.

McCabe, P. (2008). The economics of the mutual fund trading scandal. *Federal Reserve Board Working Paper*, 1–74.

Nanda, V. and K. Wei (2018). Correlated Flows, Portfolio Similarity and Mutual Fund Liquidity Management. *Working Paper*, 1–64.

Rey, H. (2015). Dilemma not Trilemma: The Global Financial Cycle and Monetary Policy Independence. *NBER*, 1–42.

Roth, J., P. H. C. Sant'Anna, A. Bilinski, and J. Poe (2023). What's trending in difference-in-differences? a synthesis of the recent econometrics literature. *Journal of Econometrics 235*(2), 2218–2244.

Rzeźnik, A. (2025). Active liquidity management, strategic complementarities, and market price of liquidity. *Management Science Forthcoming*, 1–66.

SEC (2016). Investment Company Liquidity Risk Management Programs.

Shive, S. and H. Yun (2013). Are mutual funds sitting ducks? *Journal of Financial Economics 107*(1), 220–237.

Sun, L. and S. Abraham (2021). Estimating dynamic treatment effects in event studies with heterogeneous treatment effects. *Journal of Econometrics 225*(2), 175–199.

Vayanos, D. (2004). Flight to quality, flight to liquidity, and the pricing of risk. *NBER Working Paper 10327*, 1–55.

Wardlaw, M. (2020). Measuring Mutual Fund Flow Pressure As Shock to Stock Returns. *Journal of Finance 75*(6), 3221–3243.

Yagan, D. (2019). Employment Hysteresis from the Great Recession. *Journal of Political Economy 27*(5), 2505–2558.

Zeng, Y. (2018). A Dynamic Theory of Mutual Fund Runs and Liquidity Management. *University of Washington Working Paper*, 1–75.

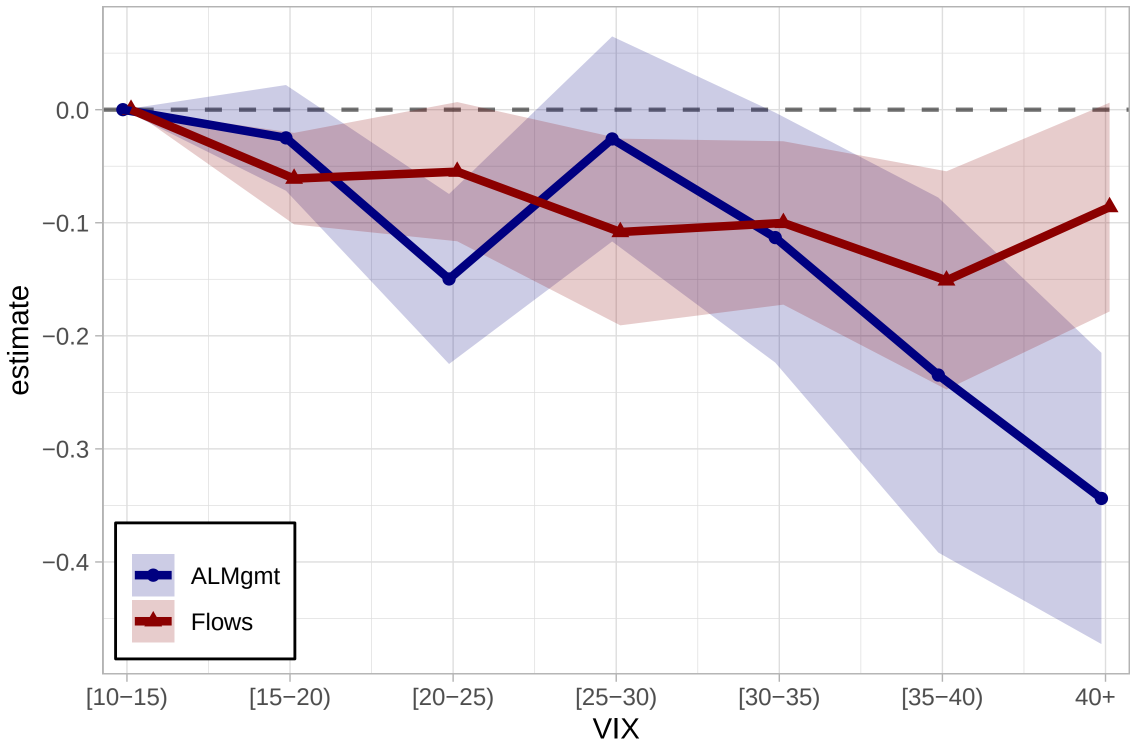
Figure 1: The effect of CGJ and peer fragility on mutual fund liquidity preferences and investor flows for different levels of VIX

This figure plots the regression coefficient δ_1^g from a panel regression of the following form:

$$\mathrm{Y}_{f,t} = \sum_{g=1}^{7} \delta_1^g \mathrm{Fragility}_{f,t-1} \times \mathrm{D}_t^g + \delta_2 \mathrm{Fragility}_{f,t} + \mathrm{X}'_{f,t-1}\Gamma_1 + \mathrm{G}_f + \mathrm{G}_t + \eta_{f,t},$$

where $\mathrm{Y}_{f,t}$ is either mutual fund active liquidity management measure or investor flows. $\mathrm{Fragility}_{f,t-1}$ is CGJ fragility index, High Fragility $\mathrm{Index}_{f,t-1}$, in Panel (a), and peer fragility index, High Peer $\mathrm{Index}_{f,t-1}$, in Panel (b). D_t^g is a dummy variable equal to one if VIX in month t belongs to volatility bin g. There are seven VIX bins with 5-unit increments. We use the lowest group ($g = 1$) with VIX levels between 10 and 15 as a reference group. $\mathrm{X}_{f,t-1}$ is a vector of one-month lagged control variables that includes: fund's alpha, log of TNA, portfolio's volatility beta, expense ratio, and Nanda and Wei's (2018) overlap management measure. We include fund, G_f, and year-month, G_t, fixed effects. We use blue dots to depict the δ_1^g coefficient estimates from active liquidity management regression. The blue-shaded areas represent 95% confidence intervals. The red triangles plot the δ_1^g coefficient estimates from mutual fund net-flows regression. The red-shaded areas represent 95% confidence intervals. The standard errors are clustered at the fund and year×month levels.

(a) The effect of *CGJ* fragility on mutual fund liquidity preferences and investor flows



(b) The effect of *peer* fragility on mutual fund liquidity preferences and investor flows

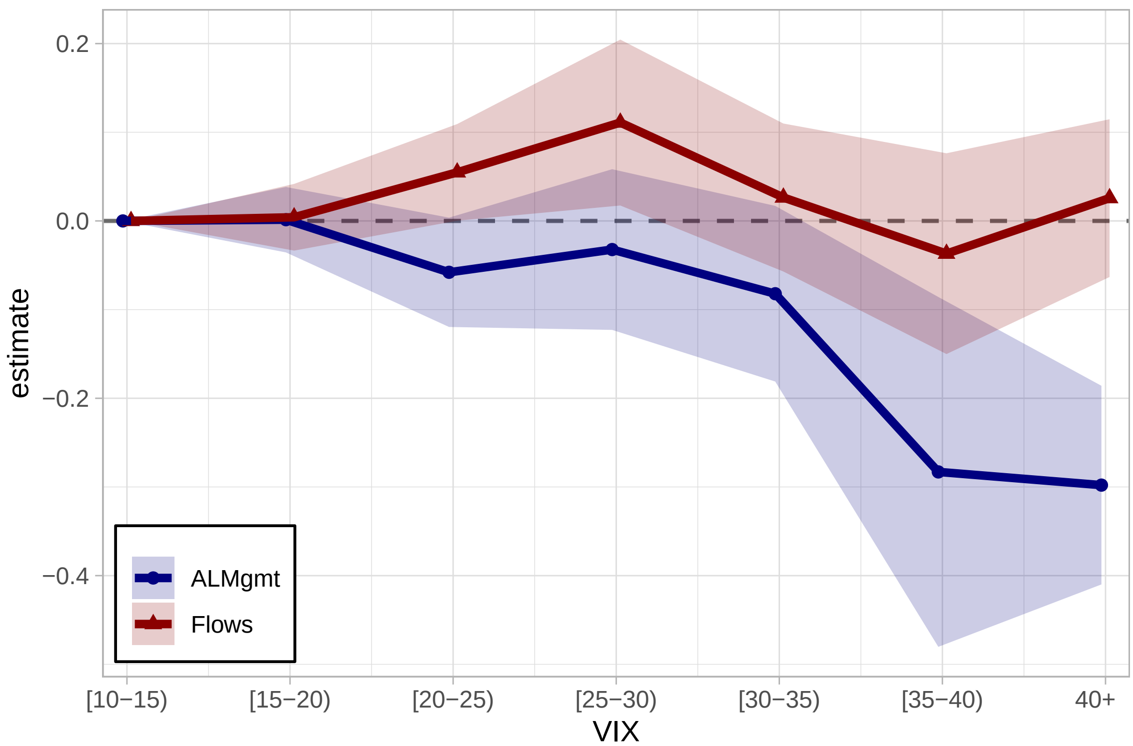


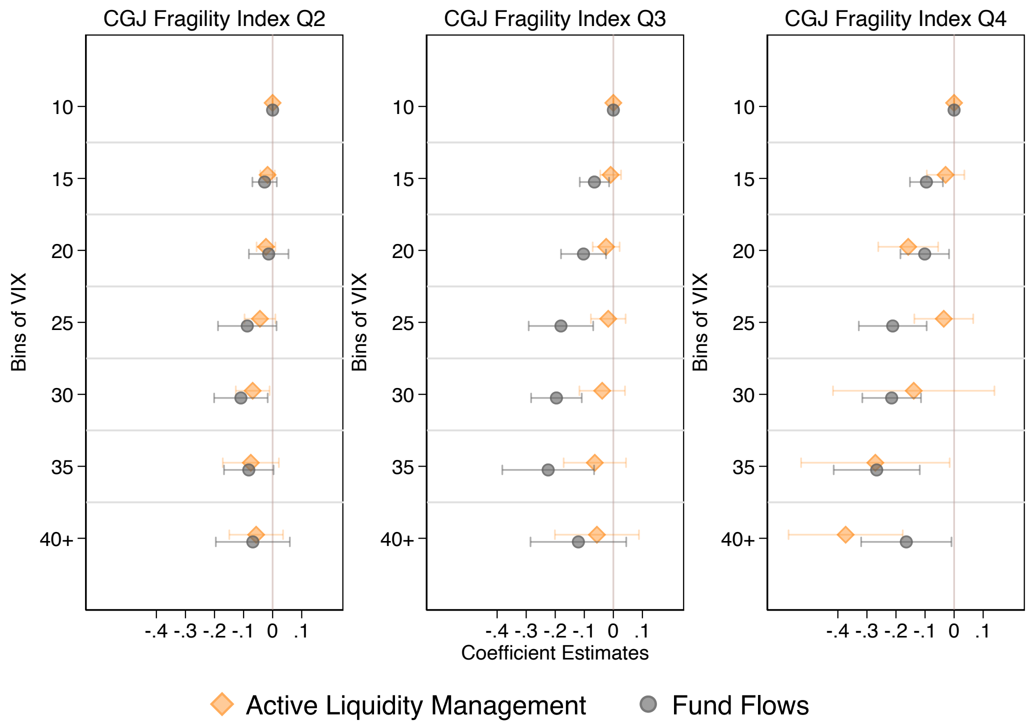
Figure 2: The effect of the quartiles of mutual fund fragility exposure and VIX bins on mutual fund active liquidity management and net-flows

This figure plots the coefficient estimates γ_{ig} from a panel regression of the following form:

$$\mathrm{Y}_{f,t} = \sum_{i=2}^{4}\sum_{g=2}^{7}\gamma_{iv}\text{Fragility Quartile}^{i}_{f,t-1} \times \mathrm{D}^{g}_{t} + \sum_{i=2}^{4}\gamma_{i}\text{Fragility Quartile}^{i}_{f,t-1} + \mathrm{X}'_{f,t-1}\Gamma_1 + \mathrm{G}_f + \mathrm{G}_t + \eta_{f,t},$$

where $\mathrm{Y}_{f,t}$ is either mutual fund active liquidity management measure or investor net-flows. In Panel (a), Fragility Quartile$^{i}_{f,t-1}$ is a dummy variable that takes a value of one if fund f's CGJ fragility index in month $t-1$, Fragility Index$_{f,t-1}$, belongs to ith quartile of CGJ fragility index distribution, otherwise zero. In Panel (b), Fragility Quartile$^{i}_{f,t-1}$ is a dummy variable that takes a value of one if fund f's peer fragility index in month $t-1$, Peer Index$_{f,t-1}$, belongs to ith quartile of peer fragility index distribution, otherwise zero. D^{g}_{t} is a dummy variable equal to one if VIX in month t belongs to volatility bin g. There are seven VIX bins with 5-unit increments. We use the lowest group ($g = 1$) with VIX levels between 10 and 15 and the lowest fragility quartile as a reference group. $\mathrm{X}_{f,t-1}$ is a vector of one-month lagged control variables that includes: fund's alpha, log of TNA, portfolio's volatility beta, expense ratio, and Nanda and Wei's (2018) overlap management measure. We include fund, D_f, and year-month, D_t, fixed effects. We use orange diamonds to depict the γ_{ig} coefficient estimates from active liquidity management regression. The solid light-orange horizontal lines represent 95% confidence intervals. The grey dots plot the γ_{ig} coefficient estimates from mutual fund net-flows regression. The solid light-grey horizontal lines represent 95% confidence intervals. We cluster the standard errors at the fund and year×month levels.

(a) CGJ fragility index



(b) Peer fragility index

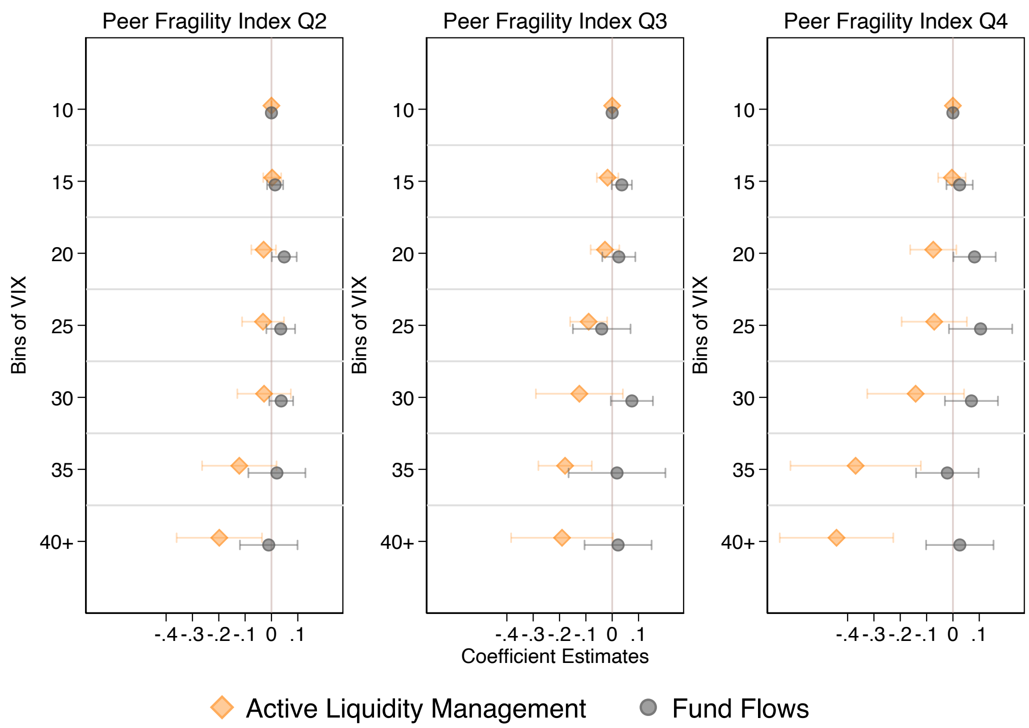


Figure 3: Mechanism of liquidity management

This figure depicts the effect of mutual fund exposure to their CGJ fragility and to peer fragility during periods of market stress on the fund's net dollar trading relative to the total net assets in Panel (a) and portfolio rebalancing in terms of liquidity in Panel (b). We sort fund's holdings into six groups based on their liquidity relative to the mean liquidity of the portfolio. 'Liquid' consists of the most liquid fund holdings, which Amihud measure in time $t-1$ is lower than lagged mean portfolio liquidity, $\text{Illiq}_{f,t-1}$, minus one standard deviation of the holdings' liquidity in the previous month, $\sigma^{\text{Illiq}}_{f,t-1}$. Group 2 comprises holdings with Amihud measure in time $t-1$ greater than $\text{Illiq}_{f,t-1} - \sigma^{\text{Illiq}}_{f,t-1}$ and smaller than $\text{Illiq}_{f,t-1} - \frac{1}{2}\sigma^{\text{Illiq}}_{f,t-1}$. Group 3 denotes holdings which lagged Amihud measure lies between $\text{Illiq}_{f,t-1} - \frac{1}{2}\sigma^{\text{Illiq}}_{f,t-1}$ and mean portfolio liquidity. Group 4 consists of fund's holdings with lagged Amihud measure between $\text{Illiq}_{f,t-1}$ and $\text{Illiq}_{f,t-1} + \frac{1}{2}\sigma^{\text{Illiq}}_{f,t-1}$. Group 5 comprises holdings with Amihud measure in time $t-1$ greater than $\text{Illiq}_{f,t-1} + \frac{1}{2}\sigma^{\text{Illiq}}_{f,t-1}$ and smaller than $\text{Illiq}_{f,t-1} + \sigma^{\text{Illiq}}_{f,t-1}$. 'Illiquid' includes the least liquid fund holdings, which Amihud measure in time $t-1$ is higher than $\text{Illiq}_{f,t-1} + \sigma^{\text{Illiq}}_{f,t-1}$. We plot the β_2 and β_4 coefficients on the interaction terms between High Fragility $\text{Index}_{f,t} \times \text{Stress}_t$ and High Peer $\text{Index}_{f,t} \times \text{Stress}_t$ from Equation (9) for each group. We use the net value of trades relative to TNA (expressed in percentages) as a LHS variable. We compute it by aggregating the value of all buys and subtracting the value of all sells over month t in each group and diving the difference by fund's TNA in $t-1$. The light-purple circles represent point estimates on the interaction term between peer fragility index and market stress indicator variable, and the light-purple solid line is the 95% confidence interval with standard errors clustered at the fund and year×month level. The grey squares denote point estimates on the interaction term between fund's own fragility index and market stress and the grey solid line is the 95% confidence interval. We use the green-shaded areas to indicate the regions of coefficient estimates that results in increased portfolio's liquidity. The red-shaded areas represent the regions of coefficient estimates that results in decreased portfolio's liquidity.

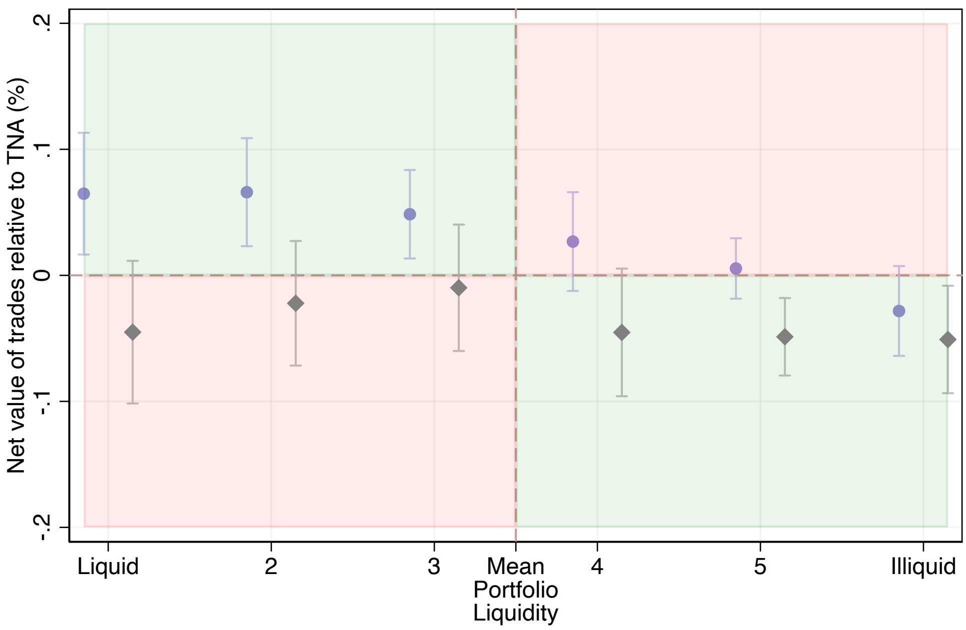


Figure 4: Volatility Shocks

The figure shows the average monthly VIX levels for our sample period: January 2002 to June 2020. The red solid lines represent volatility shocks – year-months when the VIX experiences a sudden jump with a monthly change greater than one standard deviation. We identify six such shocks and provide labels from them.

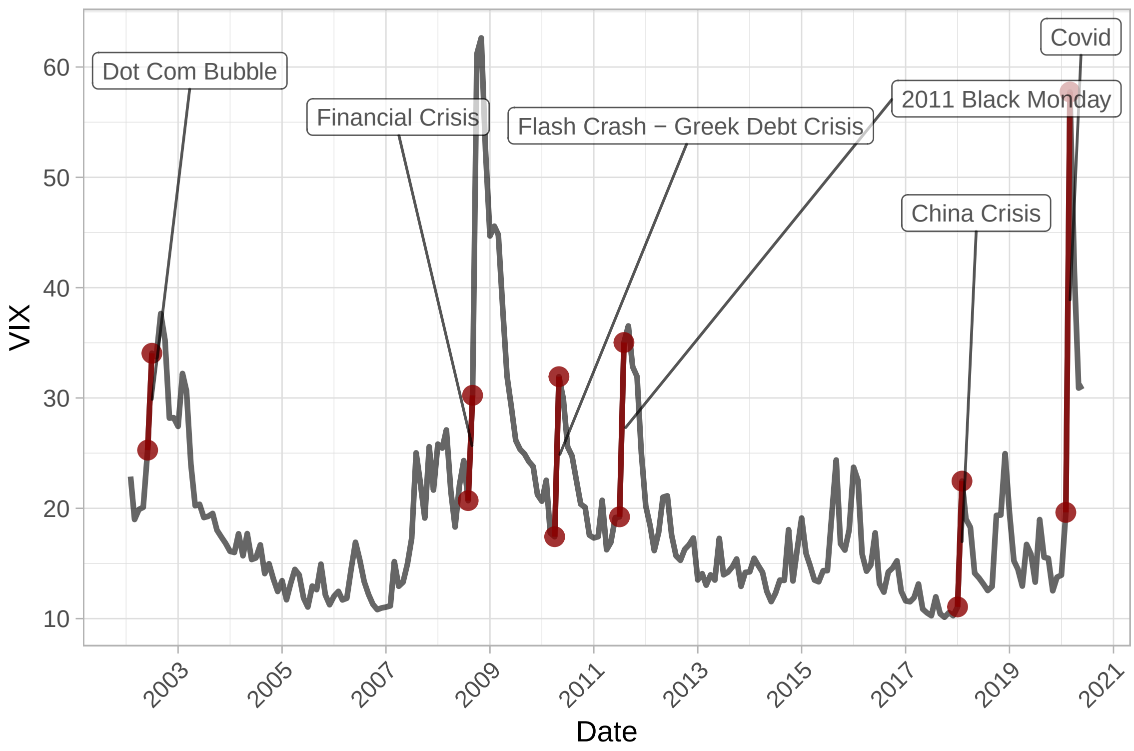


Figure 5: Panel Event Study around Volatility Shocks

This figure shows the relative effect fund's exposure to CGJ and peer fragility on investor flows and liquidity management around volatility shock events. We plot α_e and β_e regression coefficients on the interaction terms from Equation (10). We consider any monthly change in the VIX greater than a standard deviation to be a 'volatility shock.' The coefficients α_{-4} to α_4 and β_{-4} to β_4 denote the differential active liquidity management or fund net flows between (peer) fragile and non-fragile funds in the periods directly before and after the volatility shock. We use a month prior to the volatility jump ($e = -1$) as a reference period. We use Baker et al.'s (2022) 'stacked' regression estimation strategy. In the regression equation, we control for fund and year×month fixed effects. We also add a vector of one-month lagged control variables that includes: fund's alpha, log of TNA, portfolio's volatility beta, expense ratio, and Nanda and Wei's (2018) overlap management measure. The top two panels show the portfolio rebalancing in terms of liquidity of funds exposed to CGJ (top-left) and to peer fragility (top-right) around a volatility shock. The bottom two panels plot regression coefficient from investor net flow regression. The red circles represent the coefficient estimates. The light-red (dark-red) areas denote 95% (90%) confidence intervals with standard errors clustered at fund level.

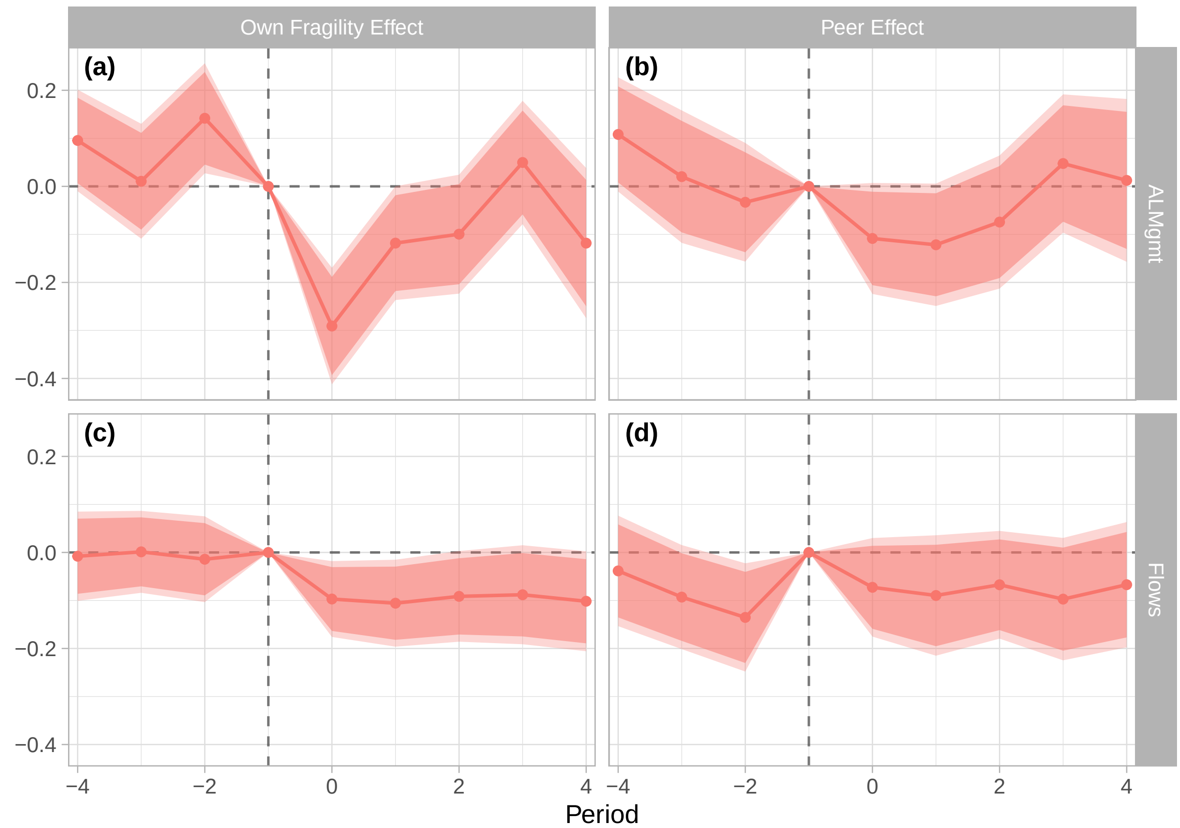


Figure 6: The effect of scandal-induced exposure to peer fragility on active liquidity management on non-scandal funds

This figure plots the regression coefficient δ_1 from cross-sectional regressions (ran every month) of the following form:

$$d\text{ALMgmt}_{f,t} = \delta_0 + \delta_1 \overline{\text{Imputed Outflows}}_f + \text{X}'_{f,t-1}\Gamma_1 + \eta_{f,t}.$$

$d\text{ALMgmt}_{f,t}$ captures the difference between non-scandal fund's active liquidity management measure at time t and the average of the variable over the September 2002 to August 2003 period. $\overline{\text{Imputed Outflows}}_f$ is an average exposure to scandal-induced fragility from September 2003 to December 2004 defined in Equation (13). $\text{X}_{f,t-1}$ indicated a vector of fund-specific controls that comprises lagged portfolio liquidity, alpha, log of TNA, portfolio's volatility beta, expenses, Nanda and Wei's (2018) overlap management measure, and contemporaneous fund net-flows. We use moving average with three-month window to smooth over monthly variability in fund's active liquidity management. The dark grey dots depict δ_1 coefficients estimates. The solid light-gray vertical lines represents 95% confidence intervals adjusted for heteroskedasticity. The orange vertical bars represent the number of newly-reported funds involved in the late trading scandal in a given month.

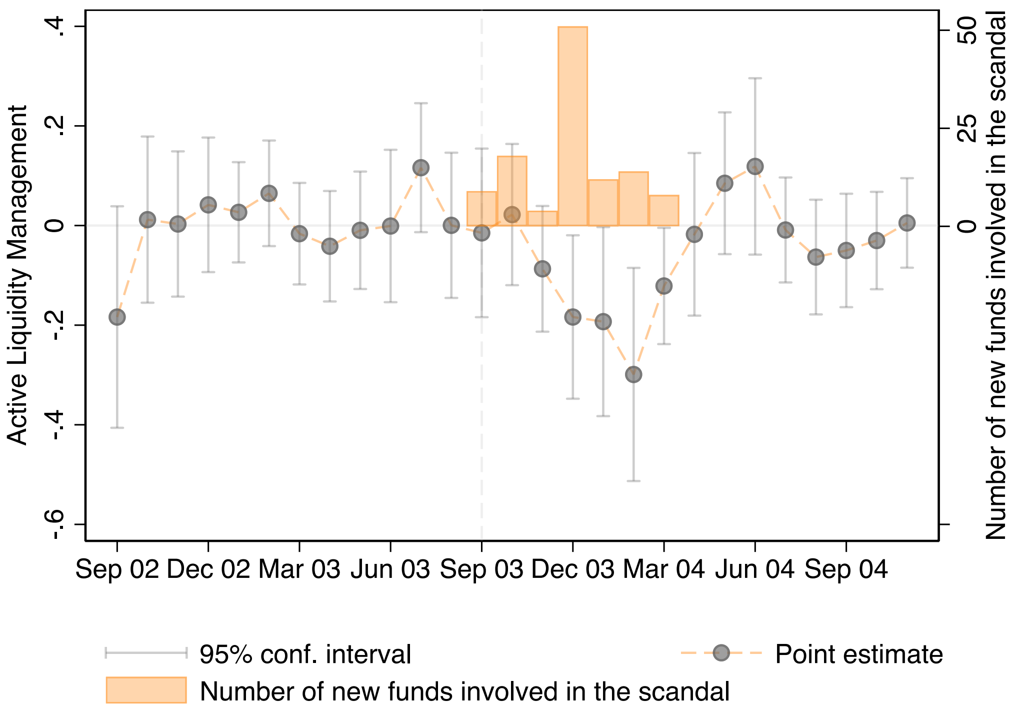


Figure 7: Active Liquidity Management, Investor Flows, and Peer Financial Fragility around Lehman Brothers Collapse

This figure plots regression coefficients ρ_{-10} to ρ_{10} from the panel regression of the following form:

$$\mathrm{Y}_{f,t} = \sum_{c=-10,\, c\neq -1}^{10} \rho_c \text{NF Peer High Exposure}_{f,t-1} \times \mathrm{D}(c)_t + \mathrm{X}'_{f,t-1}\Gamma_1 + \mathrm{G}_f + \mathrm{G}_t + \eta_{f,t}.$$

$\mathrm{Y}_{f,t}$ is either mutual fund active liquidity management measure or investor net-flows. NF Peer High Exposure$_{f,t-1}$ is a dummy variable that take a value of one if fund f's NF Peer Exposure$_{f,t-1}$ belongs to the top quartile, otherwise zero. $\mathrm{D}(c)_t$ is an indicator variable equal to one exactly c months after (or before if c is negative) the Lehman Brothers' collapse (in September 2008, $c = 0$). In the regression equation, we control for fund, G_f, and year×month, G_t, fixed effects. We also add a vector of one-month lagged control variables that includes: fund's alpha, log of TNA, portfolio's volatility beta, expense ratio, and Nanda and Wei's (2018) overlap management measure. We also control for the interaction term between fund's own exposure to financial crises, Own High Exposure$_{f,t-1}$, and the post Lehman Brothers' collapse dummy variable. The left panel plots the coefficient estimates with active liquidity management measure as a dependent variable. The right panel plots the coefficient estimates from a net-flow regression. The dark-red (light-red) shaded areas represent 90% (95%) confidence intervals with standard errors clustered at the fund level.

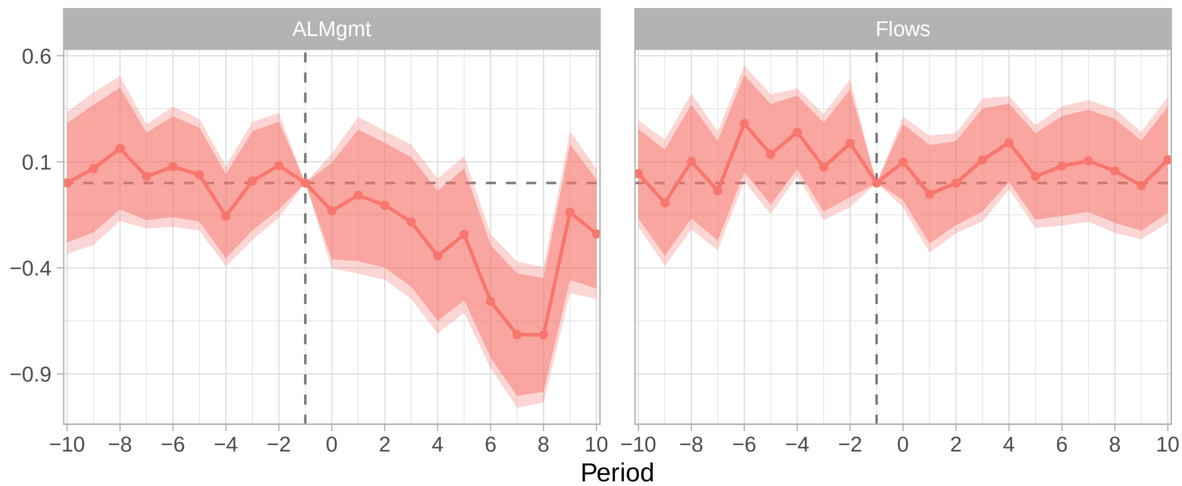


Table 1: Summary Statistics

Panel A shows summary statistics for the main fund-specific variables used in this paper. Net-Flow is fund net flows relative to its lagged total net assets (TNA). ALMgmt is fund's active liquidity management measure define in Equation (1). Cash is the percentage of fund's TNA held in form of cash. Retail is the fraction of fund's portfolio held by retail investors. Illiq is value-weighted portfolio illiquidity using with Amihud's (2002) measure. β^{liq} measures the sensitivity of mutual fund returns to market-wide innovations and is defined in Equation (2). Peer Retail is the average fraction of fund peers' portfolio held by retail investors. FtS is a value-weighted expected fire sale pressure measure, proposed by Wardlaw (2020), computed using extreme withdrawals from all funds, but fund f. CAPM-Alpha is fund's single factor alpha computed using daily returns over a previous month. TNA denotes total net assets and is expressed in millions of US dollars. β^{vol} is a mutual fund volatility beta, which is estimated with 12-month rolling window regressions of daily fund returns on the market return and change in VIX measure – see Ang et al. (2006). Expense is mutual fund expense ratio. Mgmt Overlap is Nanda and Wei's (2018) overlap management measure. Panel B reports summary statistics for the main market-wide variables used in this paper. VIX is monthly average of the CBOE Volatility Index (VIX) daily observations. R^m is the return on S& P500. Noise is a market-wide liquidity measure constructed by Hu et al. (2013). TedSpread reflects funding liquidity and is defined as the difference between 3-Month LIBOR based on US dollars and 3-Month Treasury Bill. In both panels, we report mean, median, standard deviation (SD), 1st-percentile (P1), 25th-percentile (P25), 75th-percentile (P75), 99th-percentile (P99), and the number of unique observations (NOBS) for each variable.

Panel A: Fund-specific variables	Mean	Median	SD	P1	P25	P75	P99	NOBS
Net-Flow (%)	-0.265	-0.524	4.454	-15.106	-1.427	0.582	16.468	114000
ALMgmt (·100)	0.009	0.003	0.061	-0.190	-0.004	0.017	0.258	114000
Cash (%)	2.448	1.770	2.964	-0.210	0.620	3.460	12.340	113919
Retail (%)	27.912	8.165	35.020	0.000	0.000	52.878	100.000	114000
Illiq (·100)	1.970	1.089	2.159	0.411	0.665	2.655	10.273	114000
β^{liq} (·100)	-0.246	-0.174	0.698	-2.273	-0.620	0.180	1.300	114000
Peer Retail (%)	24.367	23.661	11.677	1.199	15.950	31.927	54.014	114000
FtS	0.085	0.073	0.052	0.016	0.051	0.106	0.271	114000
CAPM-Alpha (%)	-0.006	-0.002	0.088	-0.266	-0.047	0.040	0.213	114000
TNA (in Mio.)	1621.424	422.571	4765.577	18.296	120.003	1386.864	17330.141	114000
β^{vol} (·100)	0.011	0.002	0.051	-0.088	-0.019	0.034	0.177	114000
Expense (%)	1.084	1.065	0.356	0.190	0.886	1.277	2.041	114000
Mgmt Overlap	-0.021	-0.023	0.219	-0.577	-0.153	0.108	0.553	114000

Panel B: Market-wide variables	Mean	Median	SD	P1	P25	P75	P99	NOBS
VIX	19.282	16.702	8.840	10.265	13.495	21.651	57.737	221
R^m (%)	0.548	1.106	4.221	-11.001	-1.679	2.995	9.393	221
Noise	2.605	1.935	2.463	0.885	1.495	2.675	16.004	221
TedSpread (%)	0.416	0.290	0.399	0.141	0.212	0.435	2.002	221

Table 2: Effect of CGJ and peer fragility on active liquidity management of mutual funds

This table reports OLS estimates of regressions mutual fund liquidity preferences on CGJ and peer fragility measures between 2002 and 2020. The dependent variable is active liquidity management measure, $\text{ALMgmt}_{f,t}$ defined in Equation (1). All the variables are z-scored. Our sample consists of US-domiciled mutual funds actively investing in US equities. $\text{Stress}_{f,t-1}$ is a dummy variable that takes a value of one, if VIX in month t is above 75th percentile. of the sample. We use three CGJ fragility proxies: in column (1), High Illiq $\text{Risk}_{f,t-1}$ is an indicator variable that takes a value of one if $\beta^{liq}_{f,t-1}$ is above 75th percentile, otherwise zero. $\beta^{liq}_{f,t-1}$ measures mutual fund return sensitivity to market-wide innovations in liquidity and is defined in section 3.4. In column (2), High $\text{Retail}_{f,t-1}$ is a dummy variable that takes a value of one $\text{Retail}_{f,t-1}$ is above 75th percentile, otherwise zero. $\text{Retail}_{f,t-1}$ is a percentage of retail investors in fund f in the previous month. In column (3), High $\text{Illiq}_{,ft-1}$ is an indicator variable that takes a value of one if $\text{Illiq}_{,ft-1}$ is abover 75th percentile, otherwise zero. $\text{Illiq}_{,ft-1}$ is portfolio value-weighted lagged illiquidity. In column (4), we include all three proxies. We also use two measures of peer fragility: in column (5), mutual fund's exposure to potential fire sale of stocks held by other funds, Peer $\text{FtS}_{f,t}$, defined in section 3.5. In column (6), High Peer $\text{FtS}_{f,t}$ is a dummy variable that takes a value of one if Peer $\text{FtS}_{f,t}$ is above 75th percentile, otherwise zero. Peer $\text{FtS}_{f,t}$ is mutual fund's exposure to a price pressure due to potential fire sales of other funds and id defined in section 3.5. In columns (7), High $\text{Retail}_{f,t}$ is a dummy variable that takes a value of one if Peer $\text{Retail}_{f,t}$ is above 75th percentile, otherwise zero. Peer $\text{Retail}_{f,t}$ is the average percentage of retail investors in fund f's peers in the previous month. In column (7), we include both peer fragility measures. In column (8), we regress fund's active liquidity management measure on all fragility proxies. In column (9), we combine the fragility proxies into two indices: Fragility $\text{Index}_{f,t-1}$ (defined in Equation (3)) and Peer $\text{Index}_{f,t-1}$ (defined in Equation (5)) and use them as independent variables in the $\text{ALMgmt}_{f,t}$ regression. In each regression, we include a set of one-month lagged control variables that includes: fund's alpha, log of TNA, portfolio's volatility beta, expense ratio, and Nanda and Wei's (2018) overlap management measure. We include fund and year-month fixed effects. We cluster the standard errors at the fund and year-month levels. t-statistics are reported in parentheses below the coefficient estimates. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	CGJ Fragility				Peer Fragility			All Fragility	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
High Illiq Risk$_{f,t-1}$ $\times$ Stress$_t$	-0.131***			-0.085**				-0.074*	
	(-2.94)			(-2.24)				(-1.93)	
High Retail$_{f,t-1}$ $\times$ Stress$_t$		-0.059*		-0.064**				-0.055*	
		(-1.86)		(-2.12)				(-1.85)	
High Illiq$_{f,t-1}$ $\times$ Stress$_t$			-0.165**	-0.146**				-0.122*	
			(-2.26)	(-2.07)				(-1.70)	
High Peer FtS$_{f,t-1}$ $\times$ Stress$_t$					-0.226***		-0.226***	-0.127**	
					(-3.59)		(-3.61)	(-2.03)	
High Peer Retail$_{f,t-1}$ $\times$ Stress$_t$						-0.085***	-0.086***	-0.075***	
						(-3.05)	(-3.16)	(-2.93)	
High Fragility Index$_{f,t-1}$ $\times$ Stress$_t$									-0.113**
									(-2.10)
High Peer Index$_{f,t-1}$ $\times$ Stress$_t$									-0.124***
									(-3.71)
Observations	114000	114000	114000	114000	114000	114000	114000	114000	114000
R^2	0.097	0.097	0.099	0.099	0.098	0.097	0.098	0.100	0.098
Controls:									
Fund	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects:									
Fund	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year$\times$ Month	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3: Effect of CGJ and peer fragility on mutual fund net-flows

This table reports OLS estimates of regressions mutual fund net-flows on CGJ and peer fragility measures between 2002 and 2020. The dependent variable is mutual fund net-flows, Net-Flow$_{f,t}$ and defined as TNA$_{f,t}$ − TNA$_{f,t-1} \cdot (1 + r_{f,t})$ divided by TNA$_{f,t-1}$, where TNA$_{f,t}$ is the total net assets of the fund determined at the end of the month t and $r_{f,t}$ refers to the net returns of the fund f over the month t. All the variables are z-scored. Our sample consists of US-domiciled mutual funds actively investing in US equities. Stress$_{f,t-1}$ is a dummy variable that takes a value of one, if VIX in month t is above 75th percentile. of the sample. We use three CGJ fragility proxies: in column (1), High Illiq Risk$_{f,t-1}$ is an indicator variable that takes a value of one if $\beta^{liq}_{f,t-1}$ is above 75th percentile, otherwise zero. $\beta^{liq}_{f,t-1}$ measures mutual fund return sensitivity to market-wide innovations in liquidity and is defined in section 3.4. In column (2), High Retail$_{f,t-1}$ is a dummy variable that takes a value of one Retail$_{f,t-1}$ is above 75th percentile, otherwise zero. Retail$_{f,t-1}$ is a percentage of retail investors in fund f in the previous month. In column (3), High Illiq$_{,ft-1}$ is an indicator variable that takes a value of one if Illiq$_{,ft-1}$ is abover 75th percentile, otherwise zero. Illiq$_{,ft-1}$ is portfolio value-weighted lagged illiquidity. In column (4), we include all three proxies. We also use two measures of peer fragility: in column (5), mutual fund's exposure to potential fire sale of stocks held by other funds, Peer FtS$_{f,t}$, defined in section 3.5. In column (6), High Peer FtS$_{f,t}$ is a dummy variable that takes a value of one if Peer FtS$_{f,t}$ is above 75th percentile, otherwise zero. Peer FtS$_{f,t}$ is mutual fund's exposure to a price pressure due to potential fire sales of other funds and id defined in section 3.5. In columns (7), High Retail$_{f,t}$) is a dummy variable that takes a value of one if Peer Retail$_{f,t}$ is above 75th percentile, otherwise zero. Peer Retail$_{f,t}$ is the average percentage of retail investors in fund f's peers in the previous month. In column (7), we include both peer fragility measures. In column (8), we regress fund's net-flows on all fragility proxies. In column (9), we combine the fragility proxies into two indices: Fragility Index$_{f,t-1}$ (defined in Equation (3)) and Peer Index$_{f,t-1}$ (defined in Equation (5)) and use them as independent variables in the ALMgmt$_{f,t}$ regression. In each regression, we include a set of one-month lagged control variables that includes: fund's alpha, log of TNA, portfolio's volatility beta, expense ratio, and Nanda and Wei's (2018) overlap management measure. We include fund and year-month fixed effects. We cluster the standard errors at the fund and year-month levels. t-statistics are reported in parentheses below the coefficient estimates. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	CGJ Fragility				Peer Fragility			All Fragility	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
High Illiq Risk$_{f,t-1}$ × Stress$_t$	-0.059**			-0.053*				-0.051*	
	(-2.02)			(-1.92)				(-1.84)	
High Retail$_{f,t-1}$ × Stress$_t$		-0.075**		-0.077***				-0.080***	
		(-2.56)		(-2.64)				(-2.75)	
High Illiq$_{f,t-1}$ × Stress$_t$			-0.038	-0.029				-0.025	
			(-1.10)	(-0.86)				(-0.74)	
High Peer FtS$_{f,t-1}$ × Stress$_t$					-0.039		-0.040	-0.022	
					(-1.34)		(-1.38)	(-0.76)	
High Peer Retail$_{f,t-1}$ × Stress$_t$						0.025	0.024	0.034	
						(1.00)	(0.99)	(1.36)	
High Fragility Index$_{f,t-1}$ × Stress$_t$									-0.059**
									(-2.15)
High Peer Index$_{f,t-1}$ × Stress$_t$									0.039
									(1.41)
Observations	114000	114000	114000	114000	114000	114000	114000	114000	114000
R^2	0.11	0.11	0.11	0.11	0.11	0.11	0.11	0.11	0.11
Controls:									
Fund	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects:									
Fund	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year× Month	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4: Non-Scandal Mutual Funds' Active Liquidity Management and Investor Flows – 2003 Mutual Fund Trading Scandal

This table reports coefficient estimates from OLS regressions of liquidity preferences and investor flows of non-scandal funds on their exposure to scandal-induced peer fragility. Our sample includes U.S.-domicile mutual funds actively investing in U.S. equities that were not involved in the 2003 scandal during a year following the initial scandal outbreak (from September 2003 to August 2004). The dependent variables are as follows: in columns (1) and (2), fund's active liquidity management measure defined in Equation (1) and in columns (3) and (4), investor net-flows. High Peer Scandal Exposure$_{f,t}$ is an indicator variable that takes a value of one if Imputed Outflows$_{f,t}$ (defined in Equation (12)) of non-scandal fund f in month t belong to the bottom quartile of Imputed Outflows$_{f,t}$ distribution, otherwise zero. We include fund and year-month fixed effects. In columns (2) and (4), we also add a set of one-month lagged control variables that includes: portfolio liquidity, fund alpha, log of TNA, portfolio's volatility beta, expense ratio, Nanda and Wei's (2018) overlap management measure, and investor net-flows. We cluster the standard errors at the fund level. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	ALMgmt		Flows	
	(1)	(2)	(3)	(4)
High Peer Scandal Exposure	-0.200**	-0.232**	-0.049	-0.070
	(-2.25)	(-2.59)	(-1.03)	(-1.46)
Observations	2802	2802	3718	3718
R^2	0.27	0.30	0.45	0.47
Controls:				
Fund FE	Yes	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes	Yes
Vector of fund-specific time-varying controls				
Standard Errors are clustered at:				
Fund Level	Yes	Yes	Yes	Yes

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 5: The Effect of Peer Financial Crises Exposure on Mutual Funds' Active Liquidity Management

This table reports coefficient estimates from OLS regression of mutual fund liquidity preferences on fund's exposure to peer fragility due to financial crises. Our sample includes U.S.-domicile mutual funds actively investing in U.S. equities for the 10 months post and prior September 2008. The dependent variable is fund's active liquidity management measure define in Equation (1). We use two definitions of fund's peers. In columns (1) – (4), fund's peers are 20 funds with the highest Overlap value with the fund, where the Overlap measure is computed using both financial and non-financial holdings. In columns (5) – (8), fund's peers are 20 funds with the highest Overlap value with the fund, where the Overlap measure is computed using only non-financial holdings. NF Peer Exposure (Peer Exposure) is fund f's average exposure to peer financial crises fragility before the Lehman Brothers collapse computed using only non-financial (both financial and non-financial) holdings. (NF) Peer High Exposure is a dummy variable that takes a value of one if the average of fund f's peer exposure to financial stocks before the Lehman Brothers collapse belongs to the top quartile, otherwise zero. POST_t is an indicator variable that takes a value of one after the fall of Lehman Brothers. In columns (2) – (4) and (6) – (8), we include fund and year-month fixed effects. We also control for the interaction term between fund's own exposure to financial crises and the post Lehman Brothers' collapse dummy variable and a set of one-month lagged control variables: portfolio liquidity, fund alpha, log of TNA, portfolio's volatility beta, expense ratio, Nanda and Wei's (2018) overlap management measure, and investor net-flows. We cluster the standard errors at the fund level. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	Peer Financial Exposure				NF Peer Financial Exposure			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Peer High Exposure × Post	-0.222**	-0.203**	-0.315**					
	(-2.37)	(-2.07)	(-2.41)					
Peer Exposure × Post				-0.131**				
				(-2.31)				
NF Peer High Exposure × Post					-0.344**	-0.335**	-0.442**	
					(-3.81)	(-3.58)	(-3.62)	
NF Peer Exposure × Post								-0.335**
								(-3.58)
Observations	9024	9024	6790	9024	9024	9024	6790	9024
R^2	0.23	0.23	0.24	0.23	0.23	0.23	0.24	0.23
Controls:								
Fund	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Fixed Effects:								
Fund	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year× Month	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$

Table 6: Quarterly Four-Factor Abnormal Returns and Exposure to Financial Crises

This table reports OLS estimates of cross-sectional regressions of quarterly abnormal returns of nonfinancial stocks on two dummy variables of stock's own and peer exposure to financial crises for the period between the third quarter of 2007 and the second quarter of 2009. The Carhart (1997) four-factor quarterly abnormal returns are estimated using beta loadings from monthly return regression over the 60 months from July 2003 – June 2007. Own Exposure$_{it}$ is a weighted average of a percentage of fund's portfolio invested in financial stocks calculated for the twelve months preceding Lehman Brothers collapse (from July 2007 to June 2008). We use the number of shares held by a fund of stock i at the beginning of a month as weights. Own Exposure$_i$ is a simple average of Own Exposure$_{it}$ calculated for each stock. Own High Exposure$_i$ takes a value of one if stock's own exposure belongs to the upper quartile of Own Exposure$_i$ distribution, otherwise zero. NF Peer Exposure$_{it}$ is a weighted average of a percentage of fund peers' portfolio invested in financial stocks calculated for the twelve months preceding Lehman Brothers collapse (from July 2007 to June 2008). We apply Bhattacharya et al.'s (2013) Overlap$_{f,j,t}$ for a non-financial subset of fund holdings to determine fund's peers. We use the number of shares held by a fund of stock i at the beginning of a month as weights. NF Peer Exposure$_i$ is a simple average of NF Peer Exposure$_{it}$ calculated for each stock. NF Peer High Exposure$_i$ takes a value of one if stock's peer exposure belongs to the upper quartile of NF Peer Exposure$_i$ distribution, otherwise zero. In each regression, we control for average log of market capitalization, mutual fund ownership, and the number of mutual funds holding a stock computed over the twelve months preceding the bankruptcy of Lehman Brothers (from July 2007 to June 2008). We also include industry fixed effects. Standard errors are clustered at the industry level and t-statistics are reported in parentheses below the coefficients estimates. ***, **, and * denote significance at 1%, 5%, and 10%, respectively.

	Q3/07	Q4/07	Q1/08	Q2/08	Q3/08	Q4/08	Q1/09	Q2/09
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
NF Peer High Exposure	1.397	-0.513	-0.296	-3.645	-12.068***	-8.057*	20.135	8.143
	(0.69)	(-0.21)	(-0.06)	(-1.11)	(-2.81)	(-1.76)	(1.62)	(1.31)
Own High Exposure	-1.084	0.825	-1.350	0.293	-7.040**	-7.503**	2.323	11.044**
	(-0.38)	(0.55)	(-0.45)	(0.10)	(-2.34)	(-2.13)	(0.43)	(2.34)
Observations	2732	2692	2646	2584	2530	2441	2422	2394
R^2	0.057	0.069	0.089	0.11	0.055	0.071	0.052	0.048
Controls:								
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Avg. MCap, MF Ownership, Number of MF	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Standard Errors are clustered at:								
Industry Level	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

A Appendix

Figure A.1: Panel Event Study around Volatility Shocks – An Alternative Approach This figure shows the relative effect fund's exposure to CGJ and peer fragility on investor flows and liquidity management around volatility shock events. We plot α_e and β_e regression coefficients on the interaction terms from Equation (10). We consider any monthly change in the VIX greater than a standard deviation to be a 'volatility shock.' The coefficients α_{-4} to α_4 and β_{-4} to β_4 denote the differential active liquidity management or fund net flows between (peer) fragile and non-fragile funds in the periods directly before and after the volatility shock. We use a month prior to the volatility jump ($e = -1$) as a reference period. We use Callaway and Sant'Anna's (2021) event regression estimation strategy. In the regression equation, we control for fund and year×month fixed effects. The top two panels show the portfolio rebalancing in terms of liquidity of funds exposed to CGJ (top-left) and to peer fragility (top-right) around a volatility shock. The bottom two panels plot regression coefficient from investor net flow regression. The red circles represent the coefficient estimates. The light-red (dark-red) areas denote 95% (90%) confidence intervals with standard errors clustered at fund level.

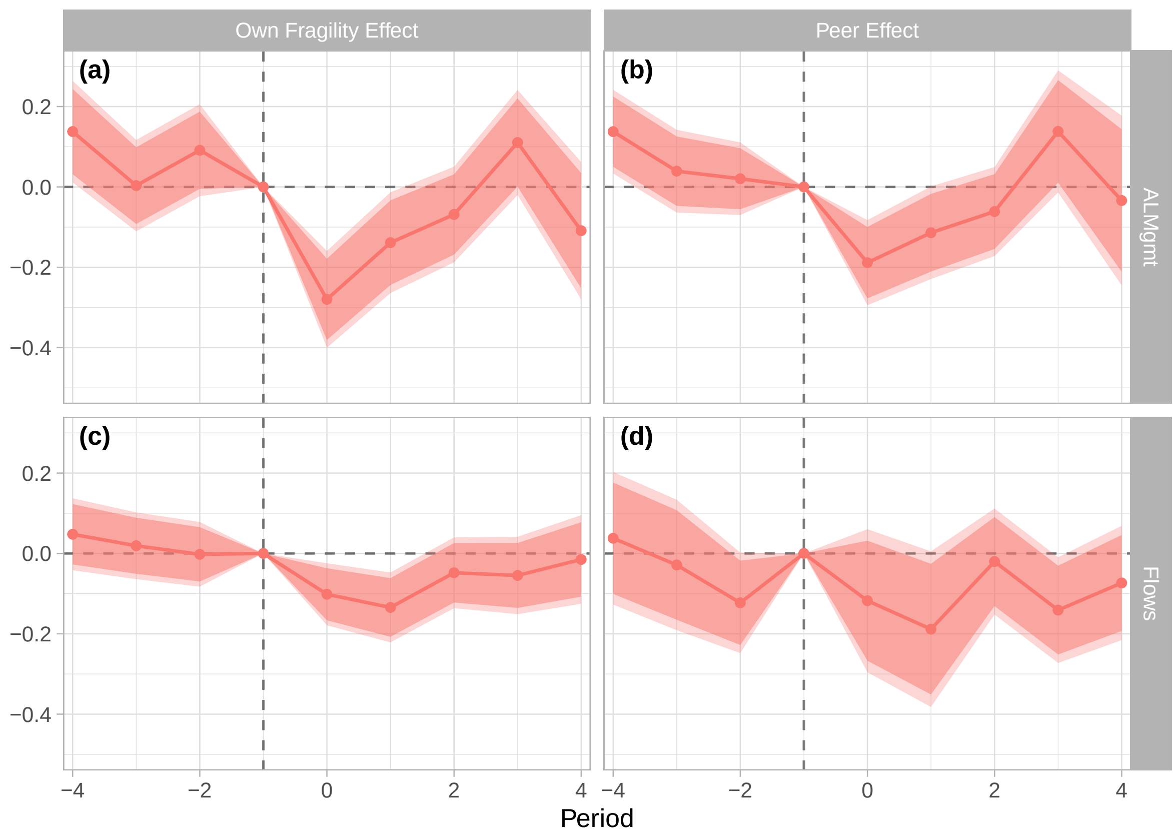


Table A.1: Cash rebalancing

This table reports OLS estimates of regressions mutual fund active liquidity management measure and cash holdings on CGJ and peer fragility measures between 2002 and 2020. The dependent variable are as follows: in column (1), active liquidity management measure, $\text{ALMgmt}_{f,t}$ defined in Equation (1), in column (2), $\Delta\text{Cash}_{f,t}$ defined as $(\text{Dollar Cash}_{f,t} - \text{Dollar Cash}_{f,t-1})/\text{TNA}_{f,t-1}$, and in column (3), Dif $\text{Cash}_{f,t}$ defined as $(\text{Dollar Cash}_{f,t}/\text{TNA}_{f,t} - \text{Dollar Cash}_{f,t-1}/\text{TNA}_{f,t-1})$. All the variables are z-scored. Our sample consists of US-domiciled mutual funds actively investing in US equities. $\text{Stress}_{f,t}$ is a dummy variable that takes a value of one, if VIX in month t is above 75th percentile. of the sample. Fragility $\text{Index}_{f,t-1}$ is CGJ fragility index and defined in Equation (3). Peer $\text{Index}_{f,t-1}$ denote peer fragility index for fund f in month $t-1$ and defined in Equation (5)). In each regression, we include a set of one-month lagged control variables that includes: fund's alpha, log of TNA, portfolio's volatility beta, expense ratio, and Nanda and Wei's (2018) overlap management measure. We include fund and year-month fixed effects. We cluster the standard errors at the fund and year-month levels. t-statistics are reported in parentheses below the coefficient estimates. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	ALMgmt	ΔCash	Dif Cash
	(1)	(2)	(3)
High Fragility $\text{Index}_{f,t-1} \times \text{Stress}_t$	-0.126***	-0.018	-0.006
	(-2.74)	(-1.04)	(-0.34)
High Peer $\text{Index}_{f,t-1} \times \text{Stress}_t$	-0.087***	-0.001	0.008
	(-2.92)	(-0.05)	(0.28)
Observations	113872	113872	113872
R^2	0.061	0.016	0.013
Controls:			
Fund	Yes	Yes	Yes
Fixed Effects:			
Fund	Yes	Yes	Yes
Year× Month	Yes	Yes	Yes

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$