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 onto other funds, linked through common asset ownership. Using data on US-equity active mutual funds, we measure peer fragility using the degree of strategic complementarities in peers' redemptions based on their investor composition and the extent to which a fund's portfolio is exposed to *expected* fire-sale pressure of other funds. We document that, similar to a fund's own strategic complementarities, funds with a higher peer fragility actively increase the liquidity of their portfolios during episodes of market stress, but not as a result of outflows. The negative externality imposed by peer fragility increases mutual fund demand for liquidity and exerts transitory price pressure, which can contribute to crisis propagation. We address potential identification concerns by exploiting variation from three natural experiments, including 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 policy makers in financial fragility caused by the liquidity transformation of institutional investors. The pricing mechanism used by open-end mutual funds might generate a first-mover advantage among their investors that amplifies the impact of negative shocks, especially during market-wide stress when market liquidity drops, and in environments in which strategic complementarities are important (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. This first-mover advantage highlights the incentives of investors to redeem if they believe other investors in the same fund will also do so. However, another strand of literature has pointed out that capital flows can force widespread trading in individual securities, resulting in institutional price pressure, which in turn affects fund performance and eventually feeds back into capital flows not only of the fund itself but also other funds (e.g., Falato, Hortaçsu, Li, and Shin, 2021).

In this paper, we study fund fragility spill-overs onto other funds, which we call 'peer fragility.' We show that peer fragility is another mechanism by which negative shocks can be amplified, particularly during times of market stress. Fragility of fund's peers poses a potential threat to the resistance of a fund portfolio and affects fund manager's portfolio allocation decisions. We begin by first showing that mutual funds actively manage the liquidity of their portfolio to mitigate the threat of financial fragility. Specifically, we show that measures of fund fragility based on proxies of strategic complementaries predict fund portfolio adjustment toward more liquid assets in times of market stress (Rzeźnik, 2020).[1]

We then create a novel peer fragility index that aims to capture the potential threat of peer withdrawals to a fund's portfolio performance and liquidity through common portfolio ownership of stocks. We document that, similar to a fund's own strategic complementaries, funds with a higher peer fragility index actively increase the liquidity of their portfolios during episodes of market stress. The index we construct integrates two dimensions of peer fragility: the degree of strategic complementarities in peers' redemptions based on peer investor composition and the extent to which a fund's portfolio is exposed to *expected* fire sale-pressure of other funds. While funds are likely to regularly incorporate peer fragility into their portfolio allocation decision, peer fragility plays an especially important role in times of market stress when the amplification of peer withdrawals has a direct effect on their own portfolio composition – but also indirectly may affect the performance and liquidity of other funds through their common ownership of stocks.

Though the mutual fund responses to these two types of fragility are similar, the underlying mechanisms driving fund's behaviour are very different. While fund's own fragility makes manifest through

[1] See also Ben-Rephael (2017), Huang (2020), and Jiang, Li, and Wang (2021).

amplified investor withdrawals (Chen et al., 2010; Goldstein, Jiang, and Ng, 2017), the peer fragility is unlikely to have a direct effect on fund's flows, but potentially can impose negative externalities on portfolio's performance and liquidity.

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. In Panel A, we focus on fund's exposure to strategic complementarities in redemption decisions proposed by Chen et al. (2010) – hereafter 'CGJ fragility.' The investor flows series (red triangles) shows that, as market volatility increases, high-CGJ fragility funds experience more outflows compared to funds with low exposure to strategic complementarities (consistent with Chen et al. (2010) and Goldstein et al. (2017)). The ALMGMT series (blue circles) reports the difference in liquidity preferences between high- and low-fragility funds. We measure liquidity preferences by using an index of 'active liquidity management' which isolates shifts in funds' average illiquidity due to portfolio composition and becomes increasingly negative as funds rebalance their portfolio toward more liquid assets. This series shows that, during times of increasing market stress (i.e., higher volatility), the liquidity preferences of CGJ fragile funds grow compared to non-fragile ones.

In Panel B of Figure 1, we show these patterns for funds grouped by their exposure to peer fragility. The ALMgmt series (blue circles) indicates that during times of increasing market stress, the demand for liquidity of high-peer fragility funds grows relative to low-peer fragility funds. The net-flow series (red triangles), however, does not show any notable differences in investors flows between funds with greater and smaller exposure to peer fragility as market stress increases. Thus, while both CGJ fragility and peer fragility are associated with greater liquidity preferences during times of market stress, their underlying mechanisms appear to be different. CGJ fragility is rooted in funds' portfolio liquidity and investor composition, and their relationship to potential redemption obligations. That is, as CGJ fragile funds experience withdrawals during market stress, they move to mitigate these threats by increasing the liquidity of their portfolios. However, Panel B documents that funds are exposed to another source of financial fragility that affects their liquidity preferences but not through redemption obligations – a fragility inherit in their links to other funds through common asset ownership.

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 origin (due to first-mover advantage among investors or peers), they actively increase portfolio's liquidity to mitigate its negative effects. The shift toward more liquid assets allows fund managers to minimize sales-induced costs imposed by (potential) future withdrawals and thus reduce the first-mover advantage in redemption decision. Intuitively, consider two funds with two very different sets of peers. The peers of the first fund are owned by small retail investors, while large institutional investors invest in the peers of the second fund. In times of market stress, the first-mover advantage in redemption decision is likely to arise among retail investors Goldstein et al. (2017). This can lead to intensified withdrawals from the peers of the first fund, forcing them to sell part of their portfolio, which in turn can affect both prices and liquidity of liquidated securities. On the other hand, large investors are expected to be less concerned about the behavior of others and less likely to redeem their money from the peers of the second fund. Thus, the first fund is exposed not only to the strategic complementarities among its own investors but also to financial fragility caused by its peers. The intensified threat of financial fragility results in an increased demand for liquidity. As the peer fragility only has an indirect effect on a mutual fund through common ownership of the same securities, we expect investor flows to remain unaffected by the exposure to peer fragility. Using data on the net flows and portfolio composition of US mutual funds actively investing in US equities from January 2002 to June 2020, we find strong support for our working hypotheses.

We start our analysis by measuring fund's exposure to strategic complementarities among investors. Consistent with the recent empirical evidence by Chen et al. (2010) and Goldstein et al. (2017), we choose the degree of portfolio's illiquidity and the composition of fund's investor as the key factors giving rise to first-mover advantage in redemption decision. We also construct a fund-specific fragility index that captures different dimensions of fund fragility and allows for interactions between portfolio liquidity and investor composition. Then, we relate the fragility measures to mutual fund liquidity preferences and investor flows during times of market stress, when market liquidity drops and strategic complementarities become especially important. We find that CGJ fragile funds actively increase liquidity portfolio compared to non-fragile funds during times of market stress. Consistent with recent empirical evidence on the first-mover advantage in redemption decision, investor outflows from fragile funds intensify during stress times. We find that fragile funds increase liquidity of the portfolio by 0.11 standard deviation during high volatility times compared to less fragile funds. Our results suggest, that in the absence of swing pricing rules (Jin, Kacperczyk, Kahraman, and Suntheim, 2022), fund managers cope with the drawbacks of strategic complementarities among their investors, by actively increasing liquidity of their portfolio.

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 to peer fragility as to their own fragility by rebalancing their portfolio toward more liquid assets. In times of market stress, peer-fragile funds actively increase liquidity of their portfolio by 0.21 standard deviation compared to funds with a lower degree of peer fragility. In contrast to CGJ fragility results, we do not observe any differential investor flow responses between funds more and less exposed to peer fragility. This result provides an evidence of a new channel through which peer fragility can affect portfolio allocation decision of a fund manager.

In our main analysis, we measure mutual fund liquidity preferences by decomposing the change in 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, 2020). 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 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, that 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 recent financial crises in 2008 and explore heterogeneity in mutual funds' and their peers' exposure to the Great Recession. We measure a fund's vulnerability by computing a percentage of a portfolio held in financial stocks (Hau and Lai, 2017). To avoid redundancy in peer definition, we use non-financial holdings to determine fund's peers. While flows do not respond to peers' financial crises exposure, fund managers actively rebalance their portfolio toward more liquid assets after the collapse of Lehman Brothers, even when we control for fund's own degree of exposure to the crises.

Given recent literature documenting propagation of financial crises by mutual funds (Manconi, Massa, and Yasuda, 2012; Hau and Lai, 2017) and the price pressure stemming from mutual fund demand for liquidity in times of market stress (Vayanos, 2004; Ben-Rephael, 2017; Rzeźnik, 2020), we investigate whether increased liquidity preferences of mutual funds exposed to fragility among their peers have any effect on prices of stocks. We further proceed with the heterogeneous variation is stock's exposure to peer fragility around the onset of the 2008 financial crises. In the four quarters preceding Lehman Brothers' collapse, neither own nor peer exposure to financial crises affect Carhart's (1997) abnormal returns. Once Lehman Brothers filed for bankruptcy in September 2008, we observe a transitory underperformance of non-financial stocks held by funds with high own financial crises exposure (by 7.04 and 7.50 bps) and funds with peers highly exposed to financial crises (by 12.07 and 8.06 bps) relative to other non-financial stocks in the third and fourth quarter of 2008. The exposure to peer fragility results in a significant negative price pressure even when we control for CGJ exposure, market capitalization, mutual fund ownership, and industry fixed effects. This result highlights the independent role of peer fragility and its importance 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), they authors show that the threat of potential outflows can create a first-mover advantage, where non-redeeming investors bear costs of redeeming investors' outflows. The incentive to withdraw money increases with portfolio's illiquidity but also with market stress. Similarly, Goldstein et al. (2017) documents that strategic complementarities among mutual fund investors strengthen when the overall market illiquidity is high which results in greater sensitivity of outflows to low performance of corporate bond funds in market stress times. Massa, Schumacher, and Wang (2021) document strategic fund's response to changes in expected financial fragility. Mutual funds rebalance away from stocks, whose investor ownership is about to become more concentrated, which, in turn, leads to a change in the composition of institutional ownership and a negative price and liquidity impact. Our paper shows that mutual funds indeed behave strategically, when exposed to fragility among their peers. By increasing the liquidity of their portfolio, they aim to mitigate the negative externalities imposed by peer fragility. Our results are complementary to Falato et al. (2021) and Chernenko and Sunderam (2020) who show that fire sales can affect fund's portfolio composition. Our contribution to this literature is to provide, to the best of our knowledge, the first empirical evidence that mutual funds respond to *potential* spillover from their peers, even though their investor flows remain unchanged.

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, times of high market uncertainty coincide with a deterioration in mutual fund performance. Consequently, redemption obligations increase when markets are volatile and fund managers put the value of flexibility before its cost by adjusting portfolios toward more liquid assets. Several recent papers (e.g., Ben-Rephael, 2017; Jiang et al., 2021; Huang, 2020; Rzeźnik, 2020) provide empirical support to the mechanism proposed by Vayanos (2004). We build on these papers and document two distinct channels explaining the increased demand for liquidity in times of market stress. We show that mutual funds are not only exposed to strategic complementarities among investors, but also to fragility among their peers. These two sources of fragility induce fund managers demand for liquidity in times of market-wide stress.

Our paper also contributes to a small but growing literature that focuses on commonalities and interdependencies across different fund portfolios. Blocher (2016) documents a positive feedback effect among mutual funds. Fund managers respond to net outflows by scaling down (at least part of) their portfolio, which potentially exerts downward price pressure on the sold securities. Thus, other funds co-holding the same securities are harmed by price depreciation and outflows from return-chasing investors, which repeats and reinforces the process. Since fund flows are predictable to a certain extent, other mutual and hedge funds might want to take advantage of or reduce the outflow-induced negative price pressure by (short-)selling stocks ahead of fire sales of distress funds (Dyakova and Verbeek, 2013; Shive and Yun, 2013). According to Nanda and Wei (2018), fund managers are aware of the network externalities and adjust their portfolio overlap with other funds when the correlation in investor flows intensifies. Building on these findings, we show that mutual funds are indirectly exposed to peer fragility, because they co-hold similar stocks. They mitigate the peer fragility risk by actively increasing liquidity of their portfolio.

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 robustness of our results. Section 6concludes.

2 Hypothesis Development

The main hypotheses we have are based on the simple premise that outside factors affect mutual fund portfolio allocation decisions. When fund managers are faced with increased market uncertainty (e.g., Ben-Rephael, 2017; Huang, 2020), strategic complementarities among investors (Chen et al., 2010; Goldstein et al., 2017; Rzeźnik, 2020), change in expected concentration of stock ownership (Massa et al., 2021), or fire sales of other funds (Falato et al., 2021), they are likely to adjust their portfolio composition to minimize the potential negative effects. Similarly, increased fragility among mutual fund peers can potentially adversely affect mutual fund performance and its liquidity. Hence, fund managers cope with their elevated exposure to peer fragility, by actively rebalancing their portfolio toward more liquid assets. This leads to the first hypothesis.

Hypothesis 1: Mutual funds with more fragile peers actively increase liquidity of their portfolio during times of market stress.

Intuitively, both the potential amplified withdrawals from peer funds and peer fire sales of joint holdings may impose a negative externality on the fund itself. Peers with higher retail ownership, where strategic complementarities are more pronounced, are more likely to experience redemptions during times of market stress. Thus, funds with retail-oriented peers are more fragile. Also, funds whose holdings are likely under sale price pressure due to fire sales of fund's peers are subject to greater 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.

The peer fragility poses a potential threat to fund's performance and portfolio's liquidity, which may not have manifested itself, yet. While strategic complementarities amplify investor withdrawals in response to poor *past* performance (Chen et al., 2010; Goldstein et al., 2017), the presence of peer fragility is less apparent to an average fund investor. Thus, peer fragility is unlikely to generate first-mover advantage in redemption decision. This leads to the second hypothesis.

Hypothesis 2: In contrast to CGJ fragility, the 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 crises, 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: The peer fragility-induced demand for liquidity during times of market stress affects stock prices.

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

3 Data and Variable Construction

3.1 Data Description

In this section, we introduce our data sources and processing procedures. We also explain the construction of the main variables used for our analysis and we discuss descriptive statistics.

3.2 Mutual fund and stock data

We use monthly mutual fund holdings obtained from Morningstar database for the period of January 2002 – May 2020. The data is compiled from both mandatory SEC filings and voluntary disclosures. We focus on domestic mutual funds actively investing in US equities. Mutual funds' total net assets (TNA), net returns, net flows, cash holdings, and other fund characteristics are also obtained from Morningstar database. For mutual funds with multiple share classes, we calculate the TNA-weighted average of net returns (cash holdings) across all share classes to derive the net return (cash holdings) of the fund. Mutual fund net flows are already available at the fund level.

The stock data (daily returns, prices, trading volumes and shares outstanding) for common shares (share code 10 and 11) are obtained from the Center for Research in Security Prices (CRSP). We use CUSIP identification number to merge mutual fund holdings information with CRSP stock database. We include only those mutual funds with at least 70% of their holdings value identified as a common U.S. equity and successfully merged with CRSP dataset. In order to measure market uncertainty, we obtain daily VIX observation from Chicago Board Options Exchange (CBOE). The resulting sample includes 1,437 distinct funds and 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.[2] 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).[3] 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 liquidity of the portfolio by trading securities. To separate these three effects, we follow Rzeźnik (2020) and perform a shift-share analysis by decomposing the change in portfolio's liquidity into three components in the following way:

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

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 individual stock's Amihud measure. The second component reflects how the shifts in holdings' prices affect 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 fund's manager. Since

[2] 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.

[3] 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-maker's liquidity provision is limited when the market volatility is high.

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 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 investor costly 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^{Mkt}_{d}, and on lead, lag, and contemporaneous innovations in market illiquidity (η^{Mkt}_{d-1}, η^{Mkt}_{d}, η^{Mkt}_{d+1}). We follow Acharya and Pedersen (2005) to construct innovations in market illiquidity and estimate the following regression:

$$r_{f,d} = \beta_0 + \beta^{\text{Mkt}}_{f,t} r^{\text{Mkt}}_{d} + \beta^{\text{Illiq}_{d-1}}_{f,t} \eta^{\text{Mkt}}_{d-1} + \beta^{\text{Illiq}_{d}}_{f,t} \eta^{\text{Mkt}}_{d} + \beta^{\text{Illiq}_{d+1}}_{f,t} \eta^{\text{Mkt}}_{d+1} + \varepsilon_{f,d}. \tag{2}$$

The mutual fund return sensitivity to market-wide innovations in liquidity, $\beta^{\text{Illiq}}_{f,t}$, is computed as a sum of $\beta^{\text{Illiq}_{d-1}}_{f,t}$,$\beta^{\text{Illiq}_{d}}_{f,t}$, and $\beta^{\text{Illiq}_{d+1}}_{f,t}$. Next, we look at the composition of mutual fund investors. When mutual funds are held by 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, $\text{Retail}_{f,t}$. 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 $\text{Illiq}_{f,t}$, $\beta^{\text{LIQ}}_{f,t}$, and $\text{Retail}_{f,t}$ to put each measure on equal footing and obtain z-scores. Our fragility index is the sum of the individual z-scores:

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

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

3.5 Peer fragility

To measure mutual fund exposure to fragility of its peers, we first have to define a set of peers for each fund every month. We use portfolio overlap measure proposed by Pool, Stoffman, and Yonker (2015):

$$\text{Overlap}_{f,j,t} = \sum_{i=1}^{\text{H}_t} \min\left(\omega_{i,f,t}, \omega_{i,j,t}\right), \tag{4}$$

where $\omega_{i,f,t}$ is fund f's portfolio weight in stock i at the end of month t, and H_t is the set of all stocks held by funds f and j as reported at the end of month t. Each month, we keep 20 funds with the largest overlap value with fund f and define them as fund f's peers. Then, we compute the average percentage of retail investors for the peers of fund f in month t, Peer $\text{Retail}_{f,t}$. We expect funds with high peer percentage of retail ownership to be more fragile – i.e., their holdings are more likely to be subject to negative price pressure stemming from retail outflow-induced sales.

We also proxy for fund's vulnerability to its peers' fragility by measuring fund's exposure to potential fire sale of stocks held by 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 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 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, Log(TNA)$_{f,t-1}$, fund's single-factor alpha, CAPM-Alpha$_{f,t-1}$, the net-expense ratio, Expense, 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.[4] 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 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 responses in terms of liquidity management to 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 marker 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 among 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:

$$\text{ALMgmt}_{f,t} = \beta_0 + \beta_1 \text{Fragility}_{f,t-1} \times \text{Stress}_t + \beta_2 \text{Fragility}_{f,t-1} + \text{X}'_{f,t-1}\Gamma_1 + \text{G}_f + \text{G}_t + \epsilon_{f,t}, \quad (6)$$

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 proxy. X$_{f,t-1}$ is a vector of fund-specific, time-varying controls that includes the natural logarithm of total net assets, TNA, fund's alpha, portfolio's volatility beta, the net-expense ratio, Expense, and Nanda and Wei's (2018) overlap management measure. G$_f$ and G$_t$ denote fund and year×month fixed effects, respectively.

[4] 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.

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 suggest 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 high 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$\times$month fixed-effects in an attempt to remove as much 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 fund, such as redemption fees, investors 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 high volatile times documented previously in the literature (Ben-Rephael, 2017; Rzeźnik, 2020). Year$\times$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, that are likely to experience substantial fire-sale price pressure due to extreme outflows from other funds, increase 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 somewhat different dimension of a fund's fragility. This 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 fund's liquidity preferences.

Finally, we combine the fund-specific and peer fragility measures into two indices: Fragility Index$_{f,t-1}$ and Peer Index$_{f,t-1}$,respectively. The two indices captures different features of fund fragility and also allow for interactions between single fragility proxies. For example, low liquidity of 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 Index$_{f,t-1}$ and Peer 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 Index$_{f,t-1}$ and Peer 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's flows, but potentially can negatively impact the value and liquidity of fund's 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 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 FtS$_{f,t-1} \times$ Stress$_t$ and Peer Retail$_{f,t-1} \times$ 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 $\text{Fragility Index}_{f,t-1}$ (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 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 fund's exposure to fragility, we estimate the following panel regression:

$$\begin{aligned}\mathrm{Y}_{f,t} \quad = \quad & \gamma_0 + \sum_{i=2}^{4}\sum_{g=2}^{7}\gamma_{ig}\text{Fragility Quartile}^{i}_{f,t-1} \times \mathrm{D}^{g}_{t} \\ & + \sum_{i=2}^{4}\gamma_i\text{Fragility Quartile}^{i}_{f,t-1} + \mathrm{X}'_{f,t-1}\Gamma + \mathrm{G}_f + \mathrm{G}_t + \eta_{f,t}, \qquad (7)\end{aligned}$$

where $\mathrm{Y}_{f,t}$ denotes either fund's active liquidity management measure or investor flows. Fragility is either CGJ fragility index, $\text{Fragility Index}_{f,t-1}$, or peer fragility index, $\text{Peer Index}_{f,t-1}$. $\text{Fragility Quartile}^{i}_{f,t-1}$ is a dummy variable that takes a value of one if fund f's $\text{Fragility Index}_{f,t-1}$ ($\text{Peer Index}_{f,t-1}$) 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 basically compare an 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 fund's peer fragility and market volatility. At the same time, investor flows should remain unaffected by 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 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 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 fund's liquidity management through common stock ownership. Consequently, mutual funds actively increase liquidity of their portfolio to reduce the potential fragility due to both investor flows and 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 portfolio's liquidity in times of market stress and when exposed to financial fragility, consistent with (Rzeźnik, 2020).

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 fund's net trading for different liquidity bins. By looking at the net trading for each liquidity bucket, we can assess whether funds increase 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 fund's 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 Value of $\text{Buys}_{f,s,t}$ (Value of $\text{Sells}_{f,s,t}$) 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:

$$\begin{aligned} \text{Net-Trade}^{l}_{f,t} \quad = \quad & \gamma_1 + \gamma_2 \text{High Fragility Index}_{f,t-1} \times \text{Stress}_t + \gamma_3 \text{High Fragility Index}_{f,t-1} \\ & + \gamma_4 \text{High Peer Index}_{f,t-1} \times \text{Stress}_t + \gamma_5 \text{High Peer Index}_{f,t-1} \\ & + \text{X}'_{f,t-1}\Gamma + \text{G}_f + \text{G}_t + \eta^{l}_{f,t}. \end{aligned} \tag{9}$$

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. Panel (a) of Figure 3 plots the γ_2 and γ_4 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 results in decreased portfolio's liquidity. The light-purple circles represent point estimates on the interaction term between peer fragility index and market stress, γ_4. The grey squares denote point estimates on the interaction between high CGJ fragility index and market stress, γ_2. 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_4 coefficient for the three top liquid bins. This suggest 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 portfolio's liquidity by net-purchasing more liquid stocks.

We also examine net-liquidity management of fragile funds within each liquidity group. We construct the net-liquidity management measure by splitting the last term in Equation (1) – the definition of ALMgmt$_{f,t}$ – into six sub-sums for each liquidity bin. We then estimate the same regression Equation (9), but use the net-liquidity management of fund f's in month t within a liquidity bin l, ALMgmt$^l_{f,t}$, as a LHS variable. We plot the γ_2 and γ_4 coefficient estimates together with 95% confidence intervals in Panel (b) of Figure 3. We observe negative and statistically significant coefficient estimates on the interaction term between High Fragility Index$_{f,t-1}$ and Stress$_t$ for the two least liquid bins ($l = 5$ and $l = 6$). This results indicates the liquidity management of CGJ fragile funds within the two least liquid groups significantly contributes to improved portfolio liquidity in times of market stress. When investigating net-liquidity management of funds exposed to peer fragility, we see that they increase portfolio's liquidity in two ways. First, similar to CGJ fragile funds, they actively increase liquidity within the least liquid group – the coefficient estimate on γ_4 is negative and significant for the illiquid bin ($l = 6$). Second, coefficient on the interaction term between High Peer Index$_{f,t}$ and Stress$_t$ is positive and significant for the second most liquid bin ($l = 2$). This means, that the sum of portfolio changes stemming from purchases weighted by Amihud measure is greater than the sum of portfolio changes due to sales weighted by stock liquidity. Combined with the estimates from Panel (a), this result suggests that peer fragile funds achieve higher portfolio liquidity by rebalancing their portfolio within the second liquidity group – i.e., net-buying of highly 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 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 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:

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

where $\mathrm{Y}_{f,e,g}$ is either 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.[5]

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

[5]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 (2022) 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 Index$_{f,e,g}$ and High Peer 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.

actively rebalance their portfolio toward more liquid stocks in response to a negative market stress shock. Regardless 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 and immediately following the volatility jump. The effect of the volatility shock on the liquidity preferences of fragile funds 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 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 allow 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 fund's 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 fund s that held the stock at the end of a previous month, where weights are defined by the volume of scandal involved 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 regression, 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 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 bring 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 follow way:

$$\text{ALM}\textsc{gmt}_{f,t} = \beta_0 + \beta_1 \text{High Peer Scandal Exposure}_{f,t} + \mathrm{X}'_{f,t-1}\Gamma_1 + \mathrm{G}_f + \mathrm{G}_t + \varepsilon_{f,t}, \tag{14}$$

where $\mathrm{X}_{f,t-1}$ 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 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 fund's liquidity preference in response to scandal-induced peer fragility, we relate investor flows of non-scandal funds to High Peer Scandal 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 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 portfolio's performance and liquidity by shifting their portfolio toward more liquid assets. However, peer fragility does not directly affect fund's flows, in contrast to a fund's own fragility that makes 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 crises 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 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 the same Overlap measure introduced in Equation (4) 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.[6] 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 Exposure$_{f,t}$. NF Peer Exposure$_{f,t}$ is fund f's exposure to peer financial crises fragility in month t. To determine fund's closest peers, we choose 20 funds with the highest non-financial-holding-based Overlap value with fund f. Then, we calculate the average percentage of financial stocks in a portfolio of fund f's peers, NF Peer Exposure$_{f,t}$. Peer Exposure$_{f,t}$ is calculated in the same way, but uses the entire mutual fund portfolio to compute the Overlap$_{f,t}$ measure.

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

$$\begin{aligned} \mathrm{Y}_{f,t} \quad = \quad & \rho_0 + \sum_{c=-10,\ c\neq -1}^{10} \rho_c \text{NF Peer High Exposure}_{f,t-1} \times \mathrm{D}(c)_t \\ & + \mathrm{X}'_{f,t-1}\Gamma_1 + \mathrm{G}_f + \mathrm{G}_t + \eta_{f,t}, \end{aligned} \tag{15}$$

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

[6] 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).

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 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 the 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:

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

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 fund's peers as 20 fund's 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 fund's 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 fund's own exposure to the Great Recession, we find that, after the collapse of Lehman Brothers, funds highly exposed to peer financial fragility actively increase 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 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 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. Fund's peers are defined based on the Overlap measure introduced in Equation (4) by using only non-financial holdings. For each quarter between July 2007 and June 2009, we run the following cross-sectional regression:

$$\text{AR}_i = \gamma_1 + \gamma_2 \text{NF Peer High Exposure}_i + \gamma_3 \text{Own High Exposure}_i + \text{X}_i' \Gamma + \text{G}_c + \zeta_i, \tag{19}$$

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 stock's average market capitalization, mutual fund ownership of shares over the number of shares outstanding, and 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-crises 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 fund 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 spillover 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 investors 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 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 results is robust to inclusion of the average financial crises 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 been already elevated, and thus, has destabilizing effect on market prices.

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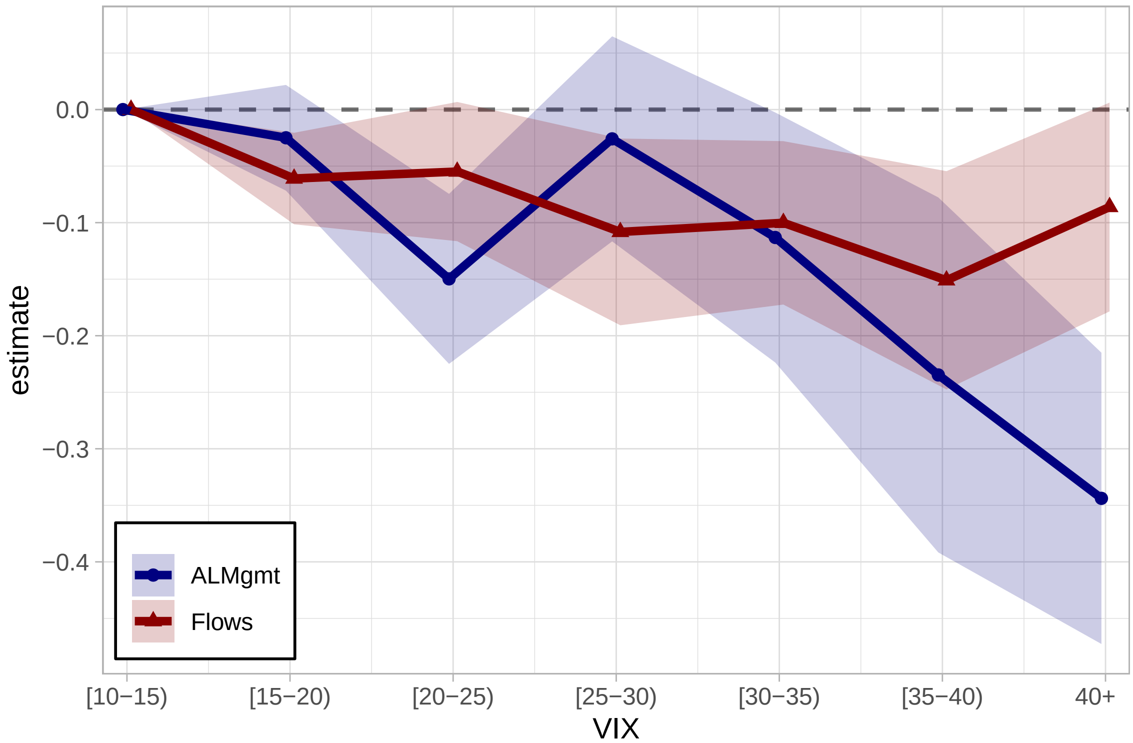
Figure 1: The effect of CGJ and peer fragility on mutual fund liquidity preferences and investor flows for different levels of VIX

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

$$\mathrm{Y}_{f,t} = \delta_0 + \sum_{g=1}^{7} \delta_1^g \text{Fragility}_{f,t-1} \times \mathrm{D}_t^g + \delta_2 \text{Fragility}_{f,t} + \mathrm{X}'_{f,t-1}\Gamma_1 + \mathrm{G}_f + \mathrm{G}_t + \eta_{f,t},$$

where $\mathrm{Y}_{f,t}$ is either mutual fund active liquidity management measure or investor flows. $\text{Fragility}_{f,t-1}$ is CGJ fragility index, High Fragility $\text{Index}_{f,t-1}$, in Panel (a), and peer fragility index, High Peer $\text{Index}_{f,t-1}$, 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

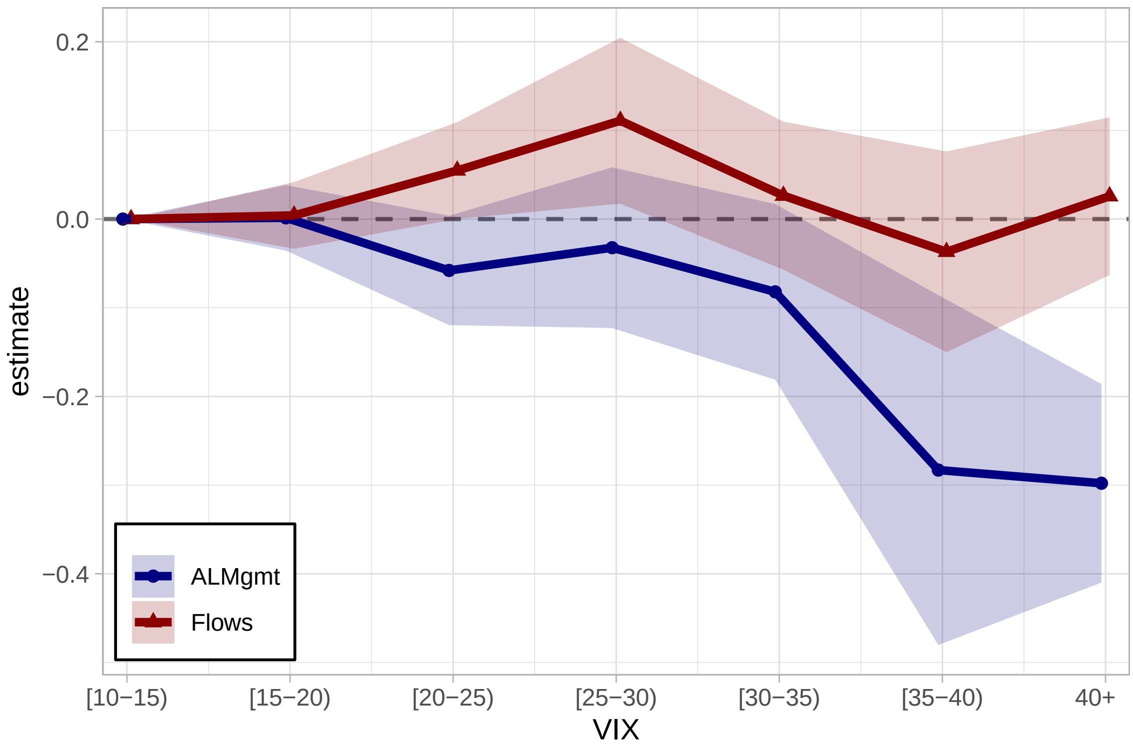


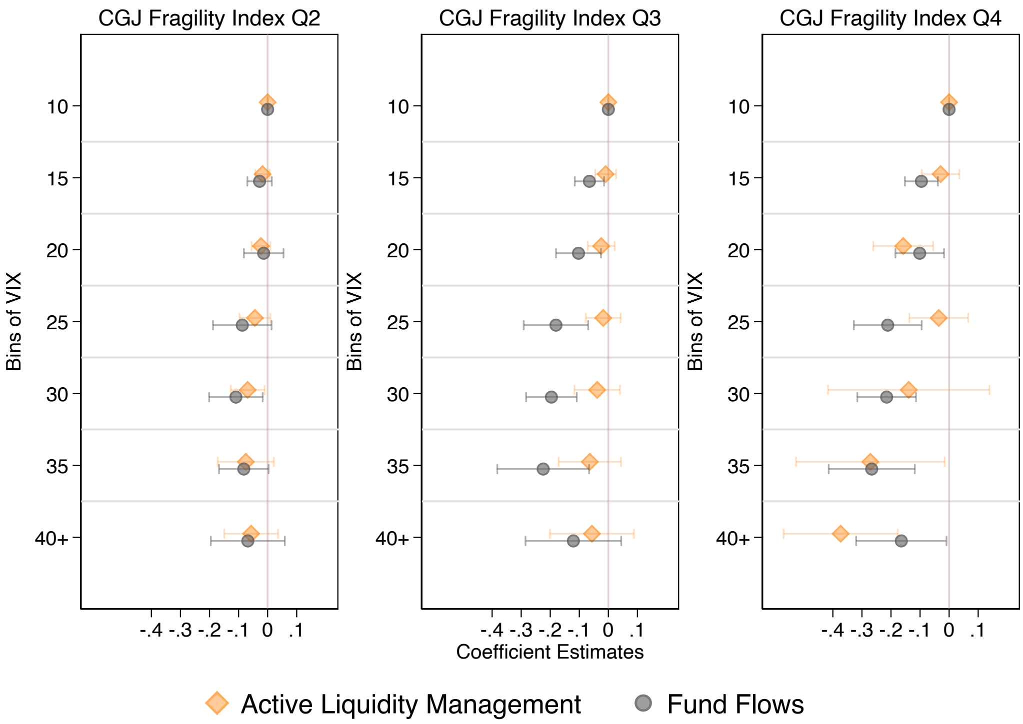
Figure 2: The effect of the quartiles of mutual fund fragility exposure and VIX bins on mutual fund active liquidity management and net-flows

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

$$\begin{aligned} \mathrm{Y}_{f,t} =& \gamma_0 + \sum_{i=2}^{4}\sum_{g=2}^{7}\gamma_{iv}\text{Fragility Quartile}^{i}_{f,t-1} \times \mathrm{D}^{g}_{t} + \sum_{i=2}^{4}\gamma_{i}\text{Fragility Quartile}^{i}_{f,t-1} \\ &+ \mathrm{X}'_{f,t-1}\Gamma_1 + \mathrm{G}_f + \mathrm{G}_t + \eta_{f,t}, \end{aligned}$$

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

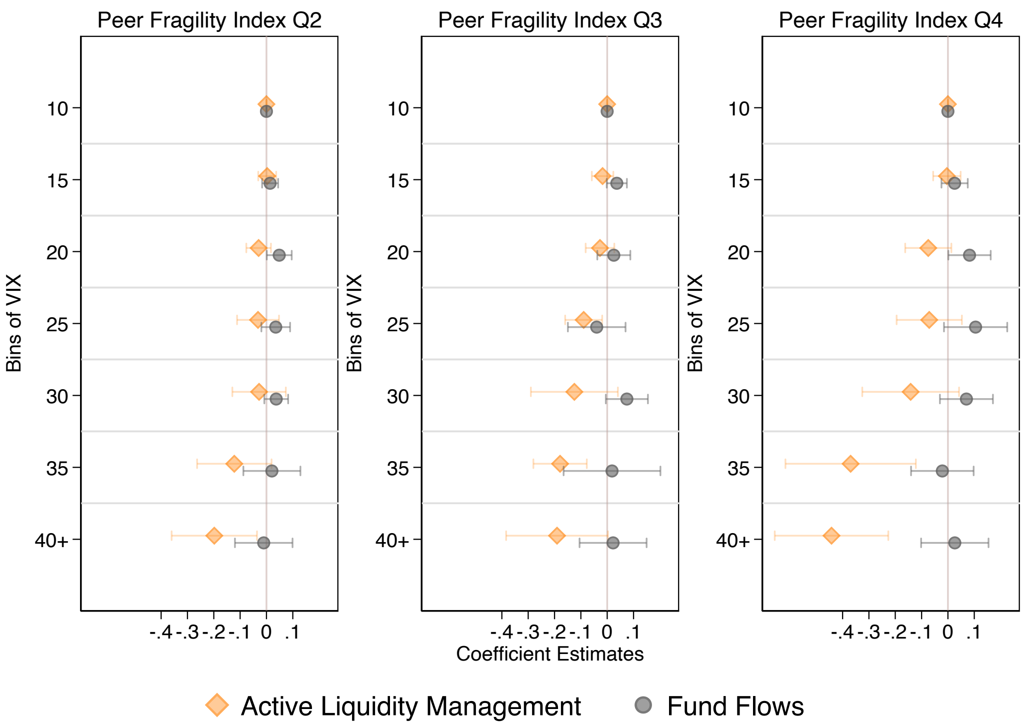
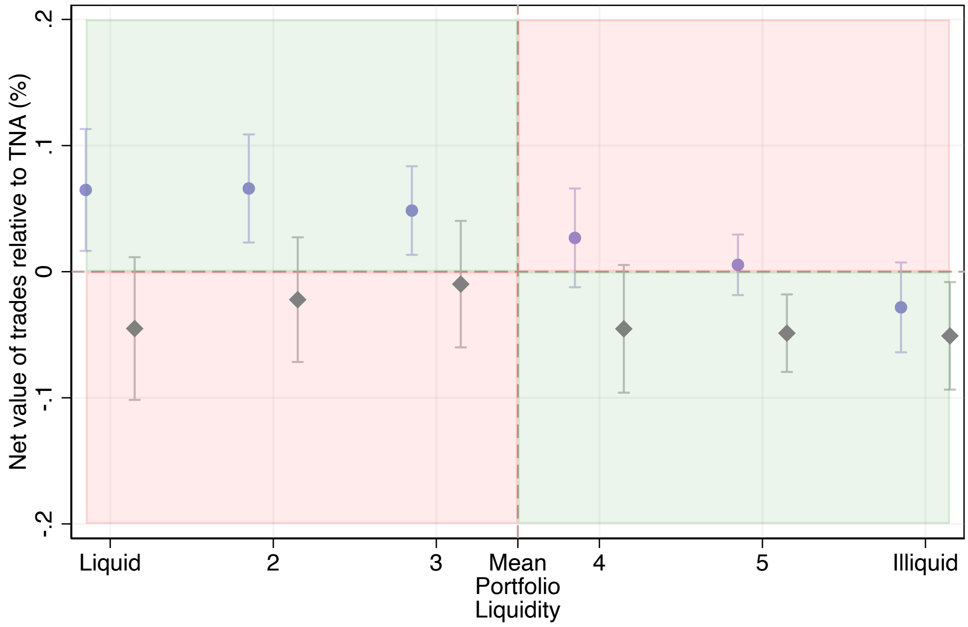


Figure 3: Mechanism of liquidity management

This figure depicts the effect of mutual fund exposure to their CGJ fragility and to peer fragility during periods of market stress on 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 holdinsg 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. In Panel (a), we use 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 $t-1$. In Panel (b), we use a net liquidity management as a dependent variable constructed in the following way. For each group, we compute a sum of changes in portfolio weights, while keeping the stock price constant, weighted by the lagged stock liquidity. 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.

(a) The net value of trades



(b) The net liquidity management

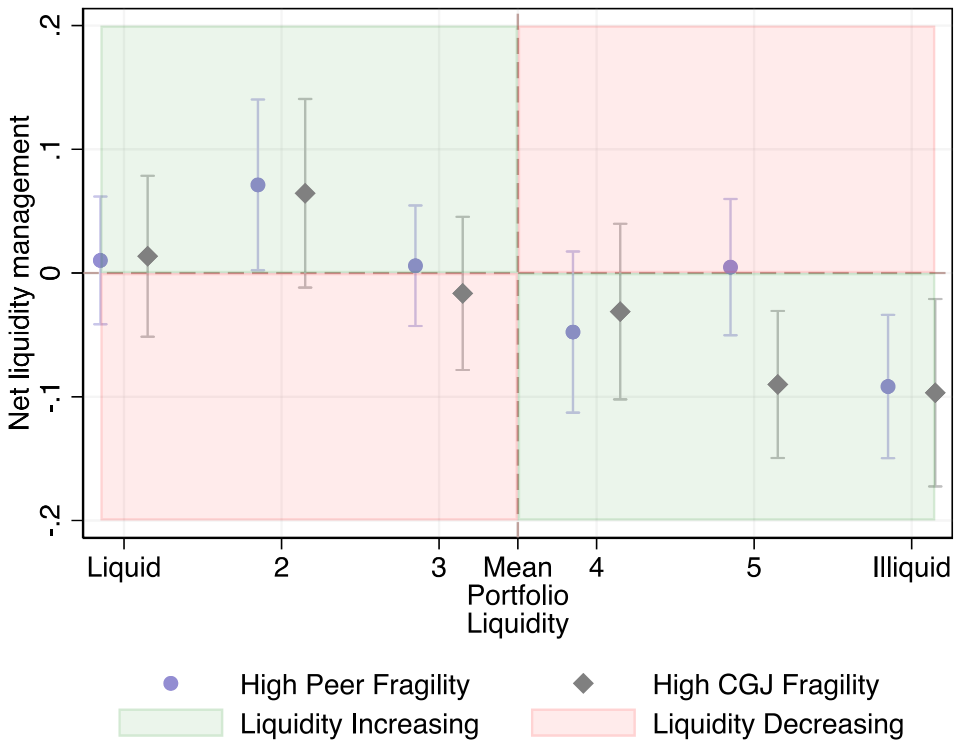


Figure 4: Volatility Shocks

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 labeles from them.

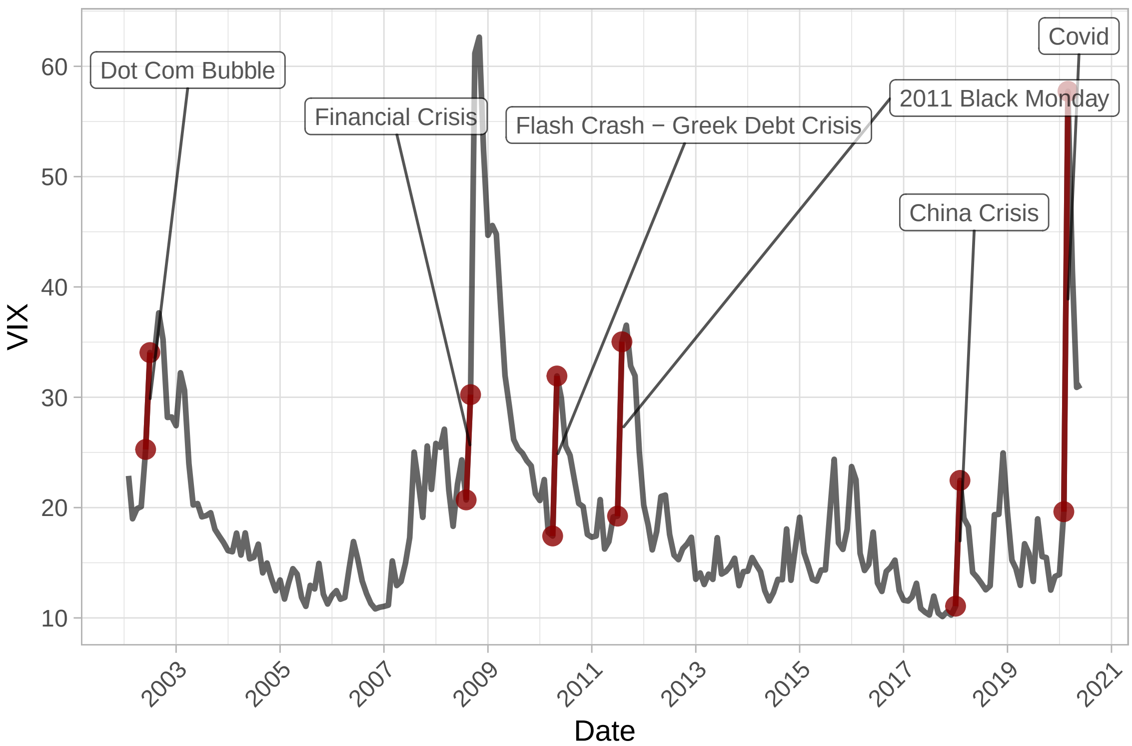


Figure 5: Panel Event Study around Volatility Shocks

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.

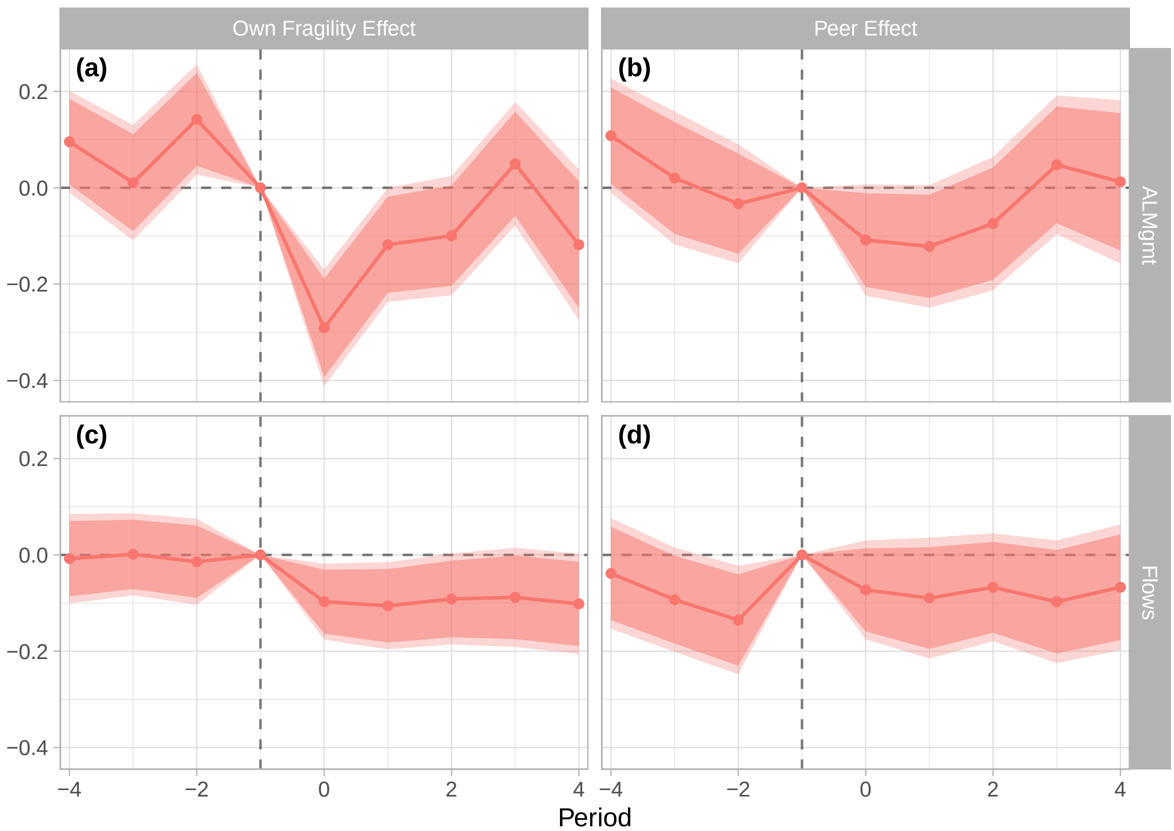


Figure 6: The effect of scandal-induced exposure to peer fragility on active liquidity management on non-scandal funds

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.

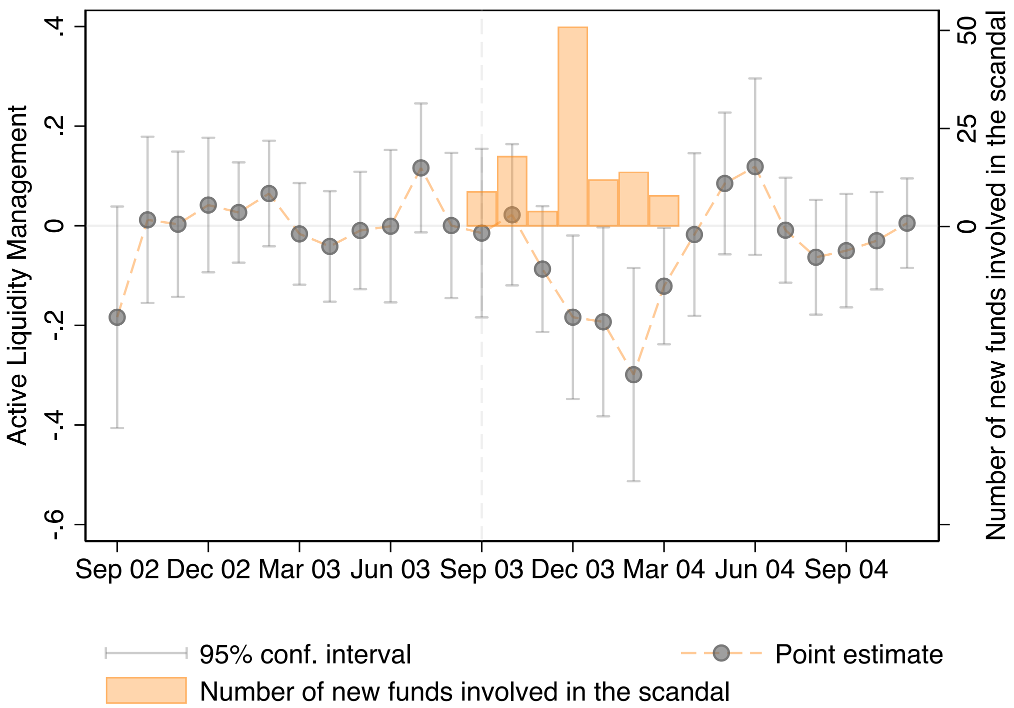


Figure 7: Active Liquidity Management, Investor Flows, and Peer Financial Fragility around Lehman Brothers Collapse

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

$$\mathrm{Y}_{f,t} = \rho_0 + \sum_{c=-10,\ c\neq -1}^{10} \rho_c \text{NF Peer High Exposure}_{f,t-1} \times \mathrm{D}(c)_t + \mathrm{X}'_{f,t-1}\Gamma_1 + \mathrm{G}_f + \mathrm{G}_t + \eta_{f,t}.$$

$\mathrm{Y}_{f,t}$ is either mutual fund active liquidity management measure or investor net-flows. NF Peer High $\text{Exposure}_{f,t-1}$ is a dummy variable that take a value of one if fund f's NF Peer $\text{Exposure}_{f,t-1}$ 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 $\text{Exposure}_{f,t-1}$, 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.

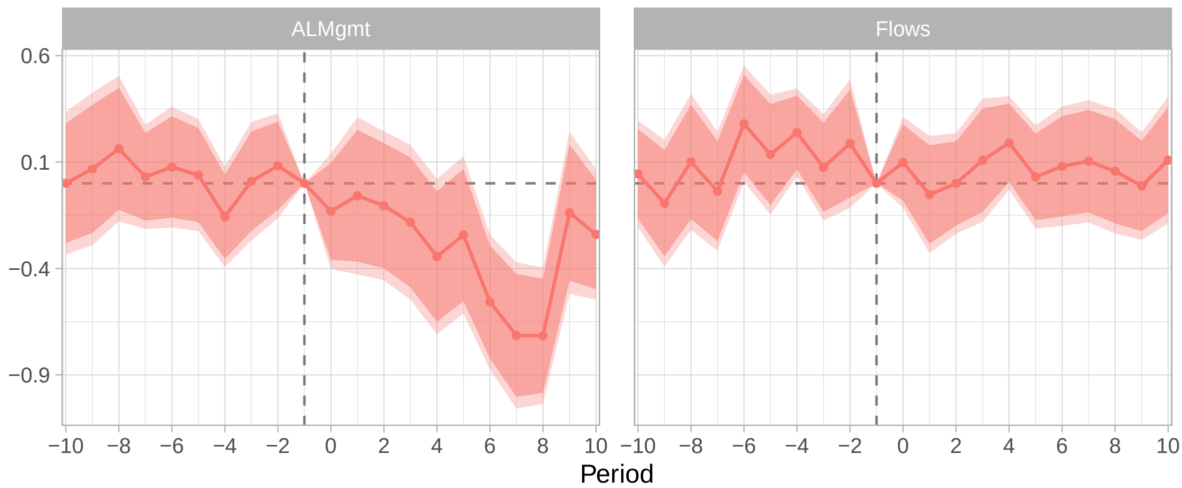


Table 1: Summary Statistics

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$_{f,t-1}$ × Stress$_t$	-0.131***			-0.085**				-0.074*	
	(-2.94)			(-2.24)				(-1.93)	
High Retail$_{f,t-1}$ × Stress$_t$		-0.059*		-0.064**				-0.055*	
		(-1.86)		(-2.12)				(-1.85)	
High Illiq$_{f,t-1}$ × Stress$_t$			-0.165**	-0.146**				-0.122*	
			(-2.26)	(-2.07)				(-1.70)	
High Peer FtS$_{f,t-1}$ × Stress$_t$					-0.226***		-0.226***	-0.127**	
					(-3.59)		(-3.61)	(-2.03)	
High Peer Retail$_{f,t-1}$ × Stress$_t$						-0.085***	-0.086***	-0.075***	
						(-3.05)	(-3.16)	(-2.93)	
High Fragility Index$_{f,t-1}$ × Stress$_t$									-0.113**
									(-2.10)
High Peer Index$_{f,t-1}$ × 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× 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 Overlap measure defined in Equation (4) and 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

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), $\text{Dif Cash}_{f,t}$ 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. $\text{Fragility Index}_{f,t-1}$ is CGJ fragility index and defined in Equation (3). $\text{Peer Index}_{f,t-1}$ 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)
$\text{High Fragility Index}_{f,t-1} \times \text{Stress}_t$	-0.126***	-0.018	-0.006
	(-2.74)	(-1.04)	(-0.34)
$\text{High Peer Index}_{f,t-1} \times \text{Stress}_t$	-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

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

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.